Risk Analysis for Climate Warming Impacts on Summer Streamflow

Final report to Bureau of Land Management

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October 10, 2012

This report is a final report for BLM on the Risk Analysis Project. As indicated in the agreed upon statement of work (SOW) dated July 16, 2010, our analysis has consisted of an evaluation of hydrologic classification for Oregon (SOW#1; item A below), a sensitivity analysis including the development of risk maps (SOW#3; B), and a streamflow modeling piece (SOW#2; C). Our progress reports, dated January 2011 and May 2011, also describe our development of a historical trend analysis for the Pacific Northwest (item D below) and a comparison of our sensitivity analysis to the regional VIC hydrologic model in support of this project (E).

We have been successful in producing products under all these items as detailed below:

A. Close consultation with EPA on development of their hydrologic landscape classification (Leibowitz, et al., 2011, Hydrological Processes & Wigington et al., in final revision, JAWRA).
B. Maps of summer streamflow sensitivity to changes in precipitation and snowmelt in conjunction with Forest Service & OWEB (Appendix A1). A manuscript describing the development and application of the maps is in preparation for submission to *Climate Change and Management* (Appendix A2).
C. Streamflow Modeling. We have developed a method for using geologic information to parameterize hydrologic models for predicting effects of climate change on streamflow. A paper describing this approach and titled: "Parameterizing sub-surface drainage with geology to improve modeling streamflow responses to climate in data limited environments" has been tentatively accepted pending final review into the journal *Hydrology and Earth System Science (Hydrol. Earth Syst. Sci. Discuss., 9, 8665-8700, 2012, www.hydrol-earth-syst-sci-discuss.net/9/8665/2012/, doi:10.5194/hessd-9-8665-2012*, Appendix A3)
D. Historical trend analysis for the Pacific Northwest. We have conducted an extensive analysis of historical streamflow trends for watersheds throughout the western U.S. using the conceptual framework described in the SOW and in Tague and Grant, 2009. Results of this analysis are included in a paper, now in final revision, that will be published by the journal *Hydrological Processes. (Safeeq et al., in press. Coupling Snowpack and Groundwater Dynamics to Interpret Historical Streamflow Trends in the Western United States,* Appendix A4)

E. A comparison of sensitivities generated by both empirical data and regional VIC hydrologic models. Poster presented at PNW Climate Change Conference, October 1&2, 2012, Boise Idaho (Appendix A5), manuscript in preparation.

In addition to preparing and publishing our findings in peer-reviewed journals, these findings have been widely disseminated through presentations at various meetings, workshops and conferences to broaden public awareness of climate change and water issues throughout region. Representative presentations included: Water and Urban Environment class, University of Oregon (10/10); "Within Our Reach" Myers Foundation forum on the Willamette River (12/10); American Geophysical Union Annual meeting (12/10); Lifelong Learning Institute, Eugene, OR (1/11); Seattle Climate Symposium (5/11); Oregon Water Conference (2 talks) (5/11); Pacific Northwest Climate Change Conference (9/11); American Geophysical Union Fall meeting, (12/11); management workshop (Region 6 Fish and Water Workshop (3/12); Central California Water Quality Monitoring Board (9/12); University seminars (OSU CEOAS seminar 1/12; OSU – LTER science meeting; 4/12); NGO and public meetings (McKenzie Watershed Council; (2/12); Eugene Water and Electric Board (2/12)); Eugene Natural History Society (3/12); McKenzie Fly Fishers Association (8/12), Pacific Northwest Climate Change Conference (10/12).

APPENDIX A1:

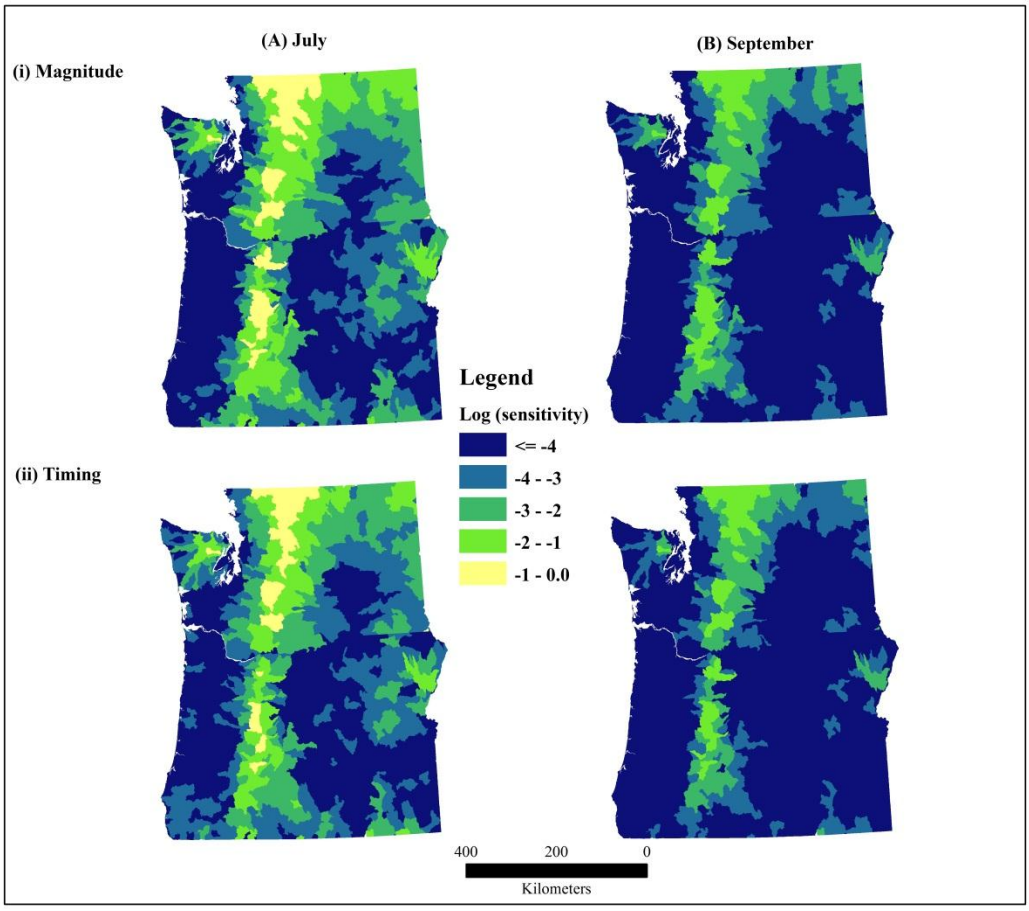

Figure: Spatial distribution of July (A) and September (B) streamflow sensitivities to a change in magnitude (i) and timing (ii) of recharge.

Summer streamflow sensitivities, defined as a change in streamflow to a change in the magnitude and timing of recharge, show a very distinct spatial pattern (Fig.1). Summer streamflow in much of the High Cascade, northern Washington, and other mountainous regions such a as the Wallowa and Blue Mountains will be the most sensitive. Beyond this, two distinct patterns emerge from this analysis. First, places [shown at the 5th field Hydrologic Unit Code (HUC) level] that are sensitive to a change in the magnitude of recharge (pk_{day}) are also sensitive to a change in the timing of recharge (t_{pk}). Second, the level of sensitivity and spatial extent of highly sensitive areas diminish as the season proceeds from early to late summer. Summer streamflow (i.e., both July and September 1st) in HUCs that receives recharge in the form of rain (e.g. Coast range and much of eastern Oregon) are less sensitive to a change in the pk_{day} or t_{pk} compared to HUCs with snowmelt driven (e.g. Cascade range and much of northern Washington recharge. This lower sensitivity primarily results from peak rainfall occurring earlier in the year, leading to a long summer recession. In places where peak rainfall occurs later in the year (e.g. eastern OR), the magnitude of recharge pk_{day} is too small to last until September 1st.

Hydrol. Earth Syst. Sci. Discuss., 9, 8665–8700, 2012
www.hydrol-earth-syst-sci-discuss.net/9/8665/2012/
doi:10.5194/hessd-9-8665-2012
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Hydrology and Earth System Sciences Discussions

This discussion paper is/has been under review for the journal Hydrology and Earth System Sciences (HESS). Please refer to the corresponding final paper in HESS if available.

Parameterizing sub-surface drainage with geology to improve modeling streamflow responses to climate in data limited environments

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Received: 7 June 2012 – Accepted: 10 June 2012 – Published: 18 July 2012

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Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

Hydrologic models are one of the core tools used to project how water resources may change under a warming climate. These models are typically applied over a range of scales, from headwater streams to higher order rivers, and for a variety of purposes, such as evaluating changes to aquatic habitat or reservoir operation. Most hydrologic models require streamflow data to calibrate subsurface drainage parameters. In many cases, long-term gage records may not be available for calibration, particularly when assessments are focused on low order stream reaches. Consequently, hydrologic modeling of climate change impacts is often performed in the absence of sufficient data to fully parameterize these hydrologic models. In this paper, we assess a geologic-based strategy for assigning drainage parameters. We examine the performance of this modeling strategy for the McKenzie River watershed in the US Oregon Cascades, a region where previous work has demonstrated sharp contrasts in hydrology based primarily on geological differences between the High and Western Cascades. Based on calibration and verification using existing streamflow data, we demonstrate that: (1) a set of streams ranging from 1st to 3rd order within the Western Cascade geologic region can share the same drainage parameter set, and (2) streams from the High Cascade geologic region, however, require a distinctive parameter set. Further, we show that a watershed comprised of a mixture of High and Western Cascade geology can be modeled without additional calibration by transferring parameters from these distinctive High and Western Cascade end-member parameter sets. Using this geologically-based parameter transfer scheme, our model predictions for all watersheds capture dominant historic streamflow patterns, and are sufficiently accurate to resolve geo-climatic differences in how these different watersheds are likely to respond to simple warming scenarios.

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1 Introduction

One of the key challenges in providing spatially distributed streamflow information is the limitation of data that is available for hydrologic model calibration and parameterization (Beven, 2001; Singh and Woolhiser, 2002; Wagener and Wheater, 2006). Implementing hydrologic models typically requires calibration of a number of drainage related parameters that cannot be directly measured (Beven, 2001). Most recent model-based studies of climate-warming impacts on hydrology within the Western US have used historic streamflow records for model calibration (Knowles and Cayan, 2002; Christensen et al., 2004; Hidalgo et al., 2009; Jung and Change, 2010; Null et al., 2010). Climate change impact assessments in the Western US address streamflow changes across multiple scales, ranging from impacts on larger-order streams that provide water supply to impacts on smaller headwater streams that support aquatic habitat. A diversity of stakeholders often needs information that includes estimates of both the distribution of headwater streamflow within a larger 3rd–4th order watershed and the discharge into larger (> 4th order) streams and reservoirs. To assess climate change impacts, estimates of how streamflow in these different sized basins responds to climate variability and change are needed (Farley et al., 2011). Particularly when assessments are focused on multiple streams, such as a population of low order stream reaches, long-term gage records may not be available for calibration. The limited availability of hydrologic data is further exacerbated by the steady decline in the USGS streamflow gauging network (USGS, 1999). Hydrologic modeling studies often assume that parameters used for a larger gaged watershed can be consistently applied to smaller sub-watersheds, or that parameters from neighboring watersheds can be used. However, calibration based on gauges from a larger order watershed does not necessarily apply to the diversity of lower order streams within that basin, or similarly, parameter transfer from neighboring watersheds may not be appropriate. In this paper we demonstrate the potential error in applying calibrated parameters across an entire watershed

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based solely on a larger order stream, and present a relatively simple strategy for parameter transfer based on geologic similarity.

Parameter transfer schemes, where parameters are assigned based on some readily measured watershed characteristics, offer one approach for assigning drainage parameters when estimates of streamflow across a range of watersheds are needed. In fact, when drainage parameters are assigned based on calibration of a larger watershed, streamflow estimates for nested subcatchments implicitly transfer parameters and assume similarity of those parameters across the larger basin. Studies on parameter transfer have used watershed size, elevation, and vegetation as a basis for transferring parameters between watersheds with varying degrees of success (e.g., Wagener and Wheater, 2006; van der Linden and Woo, 2003). These studies focus on overall model performance using different parameter schemes, but do not explicitly address implications for estimating climate change impacts. Evaluation of parameter transfer schemes, calibration approaches and model performance in general should ultimately reflect the context in which the model is being used. How good is good enough depends on the modeling goal. Here we evaluate parameter transfer approaches in the context of assessing climate change impacts on streamflow in the snow-dominated mountains of the Western Oregon Cascades.

We focus on the analysis of drainage parameter transfer in the context of snowmelt-dominated watersheds in the mountainous Western US and the use of hydrologic models to estimate how streamflow seasonality in these watersheds will respond to a warming climate. The hydrology of mountain regions throughout the globe is expected to be highly vulnerable to a warming climate (Barnett et al., 2005). In snow-dominated regions, warmer temperatures can reduce the amount of precipitation falling as snow and lead to earlier snowmelt, particularly at elevations where the majority of precipitation falls near 0 °C (Nolin and Daly, 2006). These changes in snow dynamics shift the timing of seasonal hydrographs, resulting in increased flow in winter and reductions during spring and summer (Knowles and Cayan, 2002; Barnett et al., 2005; Stewart et al., 2005). Process-based hydrologic models are one of the core tools used to

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project how water resources in these systems are likely to respond to climate variability and change. In this study, we investigate drainage parameter variation and its implication for hydrologic model-based estimates of seasonal streamflow responses to climate warming within the McKenzie River basin in Western Oregon. Our approach applies a process-based hydro-ecological model, the Regional Hydro-Ecologic Simulation System (RHESSys), and focuses on the estimation of seasonal streamflow response to climate change at multiple spatial scales. We propose an end-member mixing approach to parameter transfer where end-member sub-watersheds are defined based on geologic classification and used to estimate spatial patterns of drainage parameters. We then examine the utility of this parameter transfer strategy within the context of predicting inter-annual variation in seasonal streamflow patterns and streamflow response to climate warming in the snow-dominated watersheds of the Oregon Cascades.

2 Background

Ensemble climate model predictions for the mountain regions of the US Pacific Northwest (PNW) predict temperature increases of between 1 °C and 4 °C (Payne et al., 2004). Both empirical and model-based analyses in the PNW also link recent and projected future increases in air temperatures with reduced summer water availability (Tague et al., 2008; Hayhoe et al., 2004). This study focuses on tributaries of the McKenzie River, which is itself a tributary of the Willamette River in Oregon. The Willamette River basin is one of the largest river systems in Oregon, and drains 28 672 km^2 to its mouth at the Columbia River. The McKenzie River basin is one of several large tributaries of the Willamette that drains from the Cascade crest westward before joining the Willamette in its northward flow. The McKenzie River watershed, at 3463 km^2, accounts for approximately 12 % of the Willamette's total drainage. Streamflow within the McKenzie supports agriculture, aquatic biota, recreation, power generation, and municipal water supplies. Climate change impacts on the seasonality of flow, particularly reductions in summer flows when discharges are already low,

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will affect these water uses. Climate impact assessments for these multiple water uses will require estimates of the impact of climate variability and change in streamflow at multiple scales (Farley et al., 2011). For example, headwater reaches in the McKenzie support threatened fish species, such as Oregon Bull Trout and Chinook salmon (US EPA, 2003). At larger scales, flows are regulated by several large reservoirs primarily operated by the US Army Corps of Engineers within the McKenzie to provide power generation and flood protection.

For the McKenzie and other similar snow-dominated watersheds, a key hydrologic issue is how changing snow accumulation and snowmelt translate into changes in streamflow. There are two primary controls on this response: (1) how spatial patterns of snow accumulation and melt change and (2) how those changes in input translate into changes in streamflow behavior (Fig. 1). The latter is primarily controlled by subsurface drainage characteristics. Changes in evapotranspiration fluxes are a 3rd factor and can become increasingly important when climate change substantially alters vegetation structure through disturbances. A significant research focus in the Western US has been on improving models of snow accumulation and melt, as well as spatially explicit estimates of climate forcing functions (Daly et al., 1994). Translating these effects into streamflow change however, also requires adequate estimates of subsurface drainage characteristics. Our previous work has demonstrated that within the McKenzie, geologically mediated spatial differences in subsurface drainage characteristics can be a 1st order control on spatial patterns of streamflow response to warming (Tague and Grant, 2009). Subsurface drainage characteristics reflect both topography, which is relatively easy to parameterize given the widespread availability of DEM's, and effective subsurface conductivity of watersheds, where conductivity is a complex product of matric and macro pore flow rates and their distribution (Torch et al., 2009). In most hydrologic modeling studies, parameters associated with effective conductivity, such as hydraulic conductivity and macropore distributions, are calibrated or assumed to be spatially uniform. Given that subsurface drainage properties evolve through landscape evolutionary processes, one might expect that these parameters would vary across

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geological classification. Empirical studies and models based on streamflow patterns in the Oregon Cascades support this assertion (Tague and Grant, 2004, 2009).

Within the McKenzie River basin, sharp geologic contrasts exist between two largely contiguous geologic provinces: (a) the Plio-Pleistocene High Cascades (HC) to the east, and (b) the primarily Miocene Western Cascades (WC) to the west (Sherrod and Smith, 2000). Elevations range from 400 to 1800 m in the WC and from 1500 to over 3400 m at the summits of the large stratovolcanoes in the HC. Although the HC region has the highest elevations, much of the landscape is a broad constructional platform with relatively low relief; the WC is much steeper and more dissected. Young basaltic lava flows dominate the HC province while older lava flows and volcaniclastic rocks dominate the WC province. These distinctions drive hydrologic flowpath differences and residence times (Jefferson et al., 2006). The young lava flows in the HC have exceptionally high permeability with high vertical hydraulic conductivity, resulting in a greater portion of deep groundwater flow and large volume spring discharges. The high vertical conductivity allows recharge to quickly drain through the shallow and undeveloped soils and intersect large deep aquifers, where residence times can be on the scale of years or decades (Jefferson et al., 2006). In the WC, greater drainage efficiencies due to steep lateral hydraulic gradients and shallow bedrock and clay aquitards confine recharge to the shallow subsurface region, producing quicker transfer of recharge to streamflow (Tague and Grant, 2004). These differences in flowpaths, and therefore subsurface residence times, lead to distinctively different hydrologic regimes as characterized by higher baseflows, slower recessions, and muted flood peaks in HC watersheds (Tague and Grant, 2009). During winter storm and early spring snowmelt peaks, recharge in WC regions quickly enters streams, contributing a greater portion to flow than in HC regions. During summer periods, months after the last substantial precipitation has fallen, the groundwater storage in WC systems is largely depleted (Jefferson et al., 2006), and the pattern reverses as the majority of flow in the McKenzie originates from slow-draining HC aquifers (Tague and Grant, 2004).

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Given these geologic distinctions, we hypothesize that geologic classification should be a good indicator of drainage parameters for hydrologic models. To assess whether geology can be used as an effective parameter transfer approach, we compare the estimated parameters using model calibration against streamflow across a range of scales for WC watersheds, and compare with parameters estimated for HC watersheds. We then investigate the implications of using a "generalized" WC and HC parameter set for predicting streamflow responses to warming and test model performance for a watershed that includes both HC and WC geology, where spatial patterns of drainage parameters within the watershed are assigned based on these generalized values derived from calibration of end member WC and HC watersheds. We then explore how model assessments of climate warming impacts on streamflow seasonality respond to these strategies for assigning drainage parameters.

3 Methods

RHESSys (Tague and Band, 2004) is a physically based, spatially distributed, hierarchical daily time-step model that couples watershed hydrology, vegetation growth, and soil biogeochemical cycling processes. It models both vertical and lateral hydrologic processes. RHESSys has been applied to a number of mountain catchments in the Western US, (Tague and Grant, 2009; Baron et al., 2000) and mountainous catchments in Europe (Zierl et al., 2006). Its physical treatment of rain and snow partitioning, snow melt, shallow and deep groundwater flow, and evapotranspiration make it a suitable tool for studying the impacts of global change on mountain hydrology. Details of RHESSys process representation are summarized in Tague and Band (2004).

RHESSys model inputs consist of meteorological time series data and GIS-based inputs of topography, soils, land-use, and land cover. For simplicity, we use data from a single meteorologic station as input. While this paper focuses on the role of subsurface drainage uncertainty, another key challenge in estimating streamflow in mountain environments is distributing meteorological and, in particular, precipitation data. For

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this study, we account for spatial variation in precipitation using a single meteorological station combined with widely available PRISM mean annual precipitation grids (Daly et al., 1994) to derive spatially variable estimates for daily precipitation data. For temperature, we also use the same meteorological station and adjust temperature input data based on standard elevational lapse rates. While additional meteorological stations are located within the watershed, long-term records at multiple meteorological stations are often unavailable. In contrast, approaches for interpolating climate data such as PRISM are available for wide geographic areas. Here we test how well streamflow characteristics can be predicted for different watersheds using commonly available datasets. Other GIS dataset, such as soils, land cover, and elevation, are obtained from the Oregon Geospatial Data Clearinghouse.

There are six hydrologic parameters that can be calibrated in RHESSys: two parameters control soil transmissivity (K – saturated hydraulic conductivity at the surface, and m – the decay of saturated conductivity with depth); two parameters control soil moisture holding capacity (po – pore size index, and pa – soil water potential at air entry); and two parameters control ground-water drainage (gw1 – the percentage of subsurface water that enters a deep groundwater storage, and gw2 – the rate of drainage from that compartment). The last two parameters are only included in parameterization if this deeper ground-water store is needed, i.e., for basins with HC geology (Tague and Grant, 2004). Where deep groundwater is not present, a simpler representation of subsurface drainage is obtained by setting gw1 to 0, thus using only a shallow subsurface flow representation in the watershed.

RHESSys was calibrated independently for seven gaged watersheds in the upper McKenzie basin, including two HC watersheds and five WC watersheds (Table 1, Fig. 2). The two HC watersheds are McKenzie River at Clear Lake (CLR) and Horse Creek near McKenzie Bridge (HORSE). The five WC watersheds are Budworm Creek near Belknap Springs (BUD) and Lookout Creek (HJA), along with three subwatersheds within the Lookout Creek drainage (Mack Creek, W2, and W8). The number of HC watersheds considered was limited by the availability of gaged watersheds

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with predominately HC geology in their drainage area. All seven watersheds were calibrated for two water years, following a single year of spin-up. All watersheds were run across the same 1500 randomly generated parameter sets by sampling from a uniform random distribution within realistic ranges for each of the six parameters. For 300 of 1500 parameter sets, we set gw1 equal to 0 in order to run a simpler (and more parsimonious) model. Realistic ranges for each parameter were set based on RHESSys parameter libraries. We used two performance metrics, the Nash Sutcliffe Efficiency (NSE) and the NSE of log-transformed flow (NSElog), to evaluate the parameter sets.

For each watershed, we compared the number of acceptable parameter sets as well as sensitivity of model performance to each parameter. We examine how acceptable parameter values differ between HC watersheds and WC watersheds relative to comparisons of acceptable parameter sets within WC watersheds alone. The parameter sets are considered acceptable if the NSElog value > 0.5; we also consider a more stringent criteria > 0.8. We then define our generalized HC parameter sets as those that are acceptable for both of the two HC watersheds and our generalized WC parameter sets as those that are acceptable for all of the five WC watersheds. To test model performance, we selected four calibrated parameter sets from the generally acceptable dataset and ran RHESSys for all years for which streamflow is available (> 25 water years for most watersheds).

To assess the use of geologic classification as a method for assigning hydrologic parameters, we apply RHESSys to the South Fork McKenzie (SF) watershed (comprised of both HC and WC geology, Table 1, Fig. 2). We use an end-member mixing approach, where drainage parameters within SF are assigned based on drainage parameters for "pure" WC and HC watersheds. The pure "WC" and "HC" parameters are the generally acceptable drainage parameters from the calibrations of HC and WC described above. Thus, for the portion of SF with HC geology (approximately 64 percent of the drainage area), we use parameter sets that had acceptable performance from the CLR and Horse calibrations. For the WC portion (36 percent), we use parameter sets that had acceptable performance across all five WC watersheds.

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NSE is a commonly used performance metric and values about 0.5 are often considered acceptable. Nonetheless, assessing how "good" is "good enough" depends on the application of the hydrologic model. For this study, we base our assessment of "good enough" on the ability of the model to capture changes in seasonality of streamflow with climate warming. In climate change assessment within the Western US, a frequently used measure of streamflow change with warming is the spring fraction of total annual streamflow. Studies have shown that as snowpacks decline, the late spring and early summer fraction of total annual flow also declines (Regonda et al., 2005; Stewart et al., 2005). To examine whether model performance for the SF watershed using the generalized parameter sets is "good enough", we examine the correlation between observed and modeled spring fraction of flow. We define spring as April–June. We then simulate the response of SF and other watersheds to both 2 °C and 4 °C warming scenarios (using one of the best performing parameter sets) and assess whether predicted changes are small or large relative to error in predicting historic streamflow response to inter-annual climate variability. We apply a uniform temperature increase to historic meteorologic forcing data to generate the warming scenarios. Predicted future warming scenarios in the PNW range between one and eight degrees (Mote and Salathe, 2010). We acknowledge that a uniform warming scenario is simplistic and actual climate warming will be more temporally complex; we use it here, however, to assess the sensitivity of modeled streamflow to changes in temperature, given different assumptions about drainage parameters.

4 Results

Figure 3 illustrates the cumulative performance across parameter values for each of our six calibration parameters within each of the seven calibration watersheds. Following Thorndahl et al. (2008), we examine model sensitivity to specific parameters by comparing this cumulative performance distribution with the cumulative distribution of parameter values. Sensitivity to a particular parameter is demonstrated by a shift

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of the cumulative distribution of NSE or NSElog for that parameter relative to its cumulative distribution within the calibration set (shown in Fig. 3 as a solid black line). Results were similar using the NSE performance metric so only NSElog results are shown. The greatest difference in acceptable parameter distributions occurs between HC and WC sites; this difference is present for all parameters. Relative to the WC watersheds, the HC watershed CLR shows improved performance for higher values of gw1, lower values of gw2, higher values of m, and lower values of K, which is reasonable for a slower draining system with greater proportions of infiltrated water connecting to a deeper groundwater reservoir. The HC also shows slightly different responses to air entry pressure (pa) and pore size index (po). All sites show a strong sensitivity to m (e.g., cumulative distribution of NSElog across m parameter shows the greatest departure from the distributions of parameters within the calibration data set). For the m parameter, there are also differences within the WC sites, particularly for W2. Higher values of m show improved performance in W2 relative to other WC sites. The distinctive calibrated parameters for W2 relative to other WC watersheds may suggest actual difference in drainage characteristics. We note, however, that parameters associated with W2 may alternatively reflect potential errors in stream gage measurement since previous hydrologic analysis in W2, using a water-balance approach, suggests that approximately 20 % of streamflow may be lost as deep groundwater and not captured by the gage (Waichler et al., 2005).

Table 2 summarizes the number of acceptable parameter sets for each watershed. The watersheds differ in terms of the percentage of parameter sets that achieved an acceptable level of performance, where acceptable was defined as NSElog > 0.5. HJA had the highest (72 percent) number of parameters that achieved acceptable performance, while HORSE had the lowest (2 percent). There were 173 parameter sets that were acceptable for all WC sites (10 percent of parameters; based on NSElog > 0.5 criteria). None of the parameter sets that achieved acceptable performance for the WC sites also achieved acceptable performance for the HC sites. In other words, the set of acceptable parameters for the WC sites were mutually exclusive of those for the

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HC site. Within the WC sites, however, there was substantial, although not complete, overlap of acceptable parameter sets.

There was some variation in overall performance in the calibration period between different sites. In general, sites with a larger number of acceptable parameters had higher overall performance. To try to further constrain parameter values, we consider a more stringent criteria, defined as NSElog > 0.8 (Table 2). Using these more stringent criteria, there remain 17 parameter sets that are acceptable across for BUD, HJA, MACK, and W8 sites. However, W2 parameter sets do not overlap with the other sites if these more stringent criteria are used. This difference in W2 performance reflects its differing sensitivity to the *m* parameter as discussed above.

There are parameter sets that have gw1 set to 0 within those that are acceptable for BUD, HJA, MACK, and W8 using these more stringent criteria. We consider these sets to be preferable, given that they result in a simpler (more parsimonious) model because the deeper groundwater store is not used. It is worth noting that none of the acceptable parameter sets for the HC watershed have gw1 set to 0. Thus, for the HC watershed a deeper groundwater store must be included based either on the initial or more stringent criteria for parameter selection.

For validation, we randomly selected four parameter sets from those that were considered acceptable for WC and then HC sites, using the more stringent selection criteria. For BUD, HJA, MACK, and W8, we use parameter sets that met the more stringent criteria for all sites and two that did not include a deeper groundwater store (gw1 was set to 0). We consider these parameters to be examples of WC end-member parameter sets. We exclude W2 calibrations from developing the end-member WC parameter set because of their deviation from other WC watersheds and the evidence of observation error as the cause of this difference as noted above. For W2, we selected parameters that met the more stringent criteria for W2 and the initial criteria for all WC sites. For Horse and CLR, we randomly selected four parameter sets that met the more stringent criteria for both of those sites and consider these parameters to be examples of HC end-member parameters. Table 3 summarizes one of the parameter sets selected.

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Table 4 summarizes model performance for a 7-yr evaluation period that is common across all watersheds (except HORSE, which had very few years of overlap) and for a longer period using the full streamflow record available for each watershed. As expected, all watersheds show some degradation in performance over the evaluation periods relative to the two-year period used for calibration. Nonetheless, all watersheds show at least reasonable performance for the common evaluation and longest evaluation periods, with NSElog above 0.6 and NSE above 0.4 in most cases. Watersheds do differ in terms of long-term performance, with Horse and CLR showing lower NSElog values than other watersheds. We note that Horse and CLR are located farthest from the meteorologic station and thus are most susceptible to errors in spatial interpolation of precipitation.

Streamflow predictions for SF (Fig. 4), using a set of parameters transferred using the geologic end-member mixing described above, show good correspondence between observed and modeled flows. Based on our initial model implementation using this approach, streamflow predictions were consistently 20 percent lower than observed streamflow across all parameter sets. The long-term bias of 20 percent in total streamflow likely reflects a bias in input rather than drainage parameters, which tend to influence the hydrograph shape. Error in precipitation input estimates is not surprising given that precipitation inputs are based on a meteorologic station more than 27 km from SF. Although PRISM was also used to scale precipitation from the meteorologic site, PRISM grids are also relatively coarse (200 m). Since the focus of this paper is on drainage parameters, we simply applied a 20 percent increase in precipitation input to the model to account for the difference. We note, however, that the necessity of post-hoc precipitation adjustment illustrates the sensitivity to precipitation interpolation (or downscaling for GCM inputs), which is an ongoing area of research. Performance metrics for sixteen combinations of parameters (four different examples of HC end-member parameters paired with four examples of WC end-member parameters), after this precipitation adjustment, are summarized in Table 4.

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Model results for SF show relatively minor degradation in performance relative to the other watersheds that used calibrated parameters. For the common evaluation period, NSE for calibrated watersheds ranges from 0.59 to 0.69 and NSElog from 0.68 to 0.75. Performance measures for SF are within or even better than these ranges. For the longest evaluation period, SF produces performance metrics within the ranges produced by the watersheds for the calibration period. Figure 5 shows modeled streamflow for SF for one water year, using a parameter set based on our geologic end-member mixing approach. We compare this prediction to predictions using only WC or HC parameters. When SF is run as an all WC watershed, winter peaks are over predicted and summer flows under predicted. When SF is run as an all HC watershed the opposite bias occurs. Thus, when WC parameters are used for SF, we get a reasonable NSE (0.71), but a much low NSElog (0.28). When HC parameters are used for SF, we get a reasonable NSElog (0.83), but a lower NSE (0.65). Using a combination of HC/WC in the end-member mixing approach substantially improves performance and obtains high NSE and NSElog performance measures (0.83, 0.9, respectively).

If end-member drainage parameters are used, all sites show statistically significant (p-value < 0.001) relationships between observed and modeled estimates of inter-annual variation in spring fraction of annual flow (Fig. 6). Correlation coefficients of the relationship between observed and modeled inter-annual variation in spring flow fraction range from 0.6 to 0.9. Lowest correlations occur for CLR. Good correlation between observed and modeled estimates of inter-annual variation in spring fraction of annual flow suggest that the model captures historic driven climate variation in the seasonality of flow for all sites.

For most sites, model estimates of long-term means of spring fraction were not significantly different from observed values (Fig. 7a). The exception is W2, where modeled means of spring fraction were significantly higher than observed values. As noted above, W2 model results tend to over-estimate flow in general and may reflect stream gage limitations. Over estimation of spring fraction by the model would therefore be expected given that more flow occurs during the spring. Interestingly, W2 shows the

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highest correlation between historic inter-annual variations in observed versus modeled spring fraction (Fig. 6) – again suggesting that the model captures response to climate variation but that there is an overall bias in estimates of the volume of flow.

Finally, we test whether model estimates of spring fraction of flow for warming scenarios are significantly different from baseline estimates. For the 2 °C warming scenario (T2), CLR, HJA, MACK, and SF show statistically lower spring fractions. For the 4 °C warming scenario (T4), all watersheds except the more rain-dominated W2 show significant reductions (Fig. 7a). For the SF watershed, changes in streamflow with warming are large relative to model error. Further, we show that for the SF watershed, changes in spring fraction of flow are substantially different across different assumptions regarding drainage parameters (Fig. 7b). Simulations using the HC end-member watersheds show the least reduction in spring fraction of flow with warming, and also show almost no difference between T2 and T4 warming scenarios. If WC end-member parameters are used, the reduction in spring fraction of flow is greater, more variable from year to year, and shows a greater decline with more warming. Using the combined end-member approach, changes in seasonality with warming are intermediate between those found using the WC end-member and HC end-members alone. In this case, there is a moderate, though still, substantial reduction in spring fraction of flow with 2 °C warming, but with high inter-annual variation.

5 Discussion

Comparison of drainage parameter sensitivity across multiple watersheds provides insight into underlying hydrologic behavior of these watersheds, and provides a basis for deciding whether or not hydrologic parameters might be readily transferred from one watershed to another. For sites within the WC geologic region, parameter sensitivity was similar across scales ranging from a 4th order (HJA) to a 3rd order (MACK) to a 1st order (W8) watershed. However, W2 was an exception. As noted above, its parameters may also account for under representation of subsurface flow by the stream

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gage. W2 differs somewhat from W8 in receiving a higher proportion of rain versus snow events (Perkins and Jones, 2008) and parameter differences may be compensating for differences in snow accumulation and melt. We note, however, that HJA includes rain-dominated elevations and performs well with parameters from W8, which is usually snow dominated. Parameter sensitivity for HC sites was clearly distinctive from WC sites and is consistent with the interpretation presented in other modeling and empirical analyses (Tague et al., 2008; Jefferson et al., 2008) that suggest HC geology supports a slower draining, deeper groundwater system. Thus, if we remove W2 from our list of watersheds, we have two sets of parameters that correspond to end-members associated with mappable geologic regions.

The success of parameter transferability based on this mappable HC/WC classification depends on: (a) whether the HC/WC geologic classification resolves dominant spatial differences in subsurface drainage behavior; (b) whether the model representation of spatial differences in snow accumulation and melt is adequate and not implicitly corrected for by drainage parameters; and (c) whether spatial variation in other inputs, including meteorologic forcing, is adequately represented. For the SF, the necessity of adjusting incoming precipitation magnitudes suggest that the third condition is not met and more sophisticated schemes for interpolating precipitation data are needed. The relatively strong performance of SF once precipitation magnitudes (but not timing) were adjusted suggests that conditions (a) and (b) can be met within the larger McKenzie River basin. For SF and other watersheds, model performance measured as NSE or NSElog was within the range commonly reported in other model-based studies within the Western US (e.g., Hay and Clark, 2003; Franz et al., 2008; Graves and Chang, 2007).

Ultimately, the evaluation of model performance depends upon the use of that model. Here we evaluate model performance relative to an assessment of the impact of simple climate warming on seasonality of streamflow. Specifically, we examined model estimates of the spring fraction of annual flow. For most study sites, our model estimates of mean spring fraction of flow and its inter-annual variation were not significantly

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different from observed given historic climate forcing. What is particularly encouraging is that the SF watershed shows no degradation in performance relative to calibrated watersheds (based on predictions of spring fraction of flow).

Results of warming scenarios show that geology and snow vs. rain are both important factors in the sensitivity of watersheds to warming. For all snow-dominated sites, a warming of 4 °C led to a statistically significant reduction in spring fraction. For the rain-dominated site it did not. For the 2 °C warming scenario, higher and more snow-dominated watersheds, such as W8, did not show a significant reduction in spring fraction. In contrast, larger watersheds, such as HJA and MACK, that comprise a larger elevation range and include elevations typically at the boundary between rain-dominated and snow-dominated did show a reduction in spring fraction for the 2 °C warming scenario. These modeled spatial differences in the sensitivity of streamflow to warming are consistent with both empirical and model-based literature that demonstrate a linkage between reductions in spring fraction of flow, elevation, and warming for snow-dominated regions in the Western US (Stewart et al., 2005; Nolin and Daly, 2006). In addition to variation in the sensitivity of spring fraction to warming across snow-to-rain transitions, geologic differences are also important. Using the end-member drainage parameters from the WC for the SF watershed resulted in greater and more variable estimates of the reductions in spring fraction of flow with warming relative to estimates using HC drainage parameters, suggesting that greater drainage rates associated with WC geology enhance the sensitivity of the spring fraction of flow to warming. These results are consistent with our earlier model-based analysis that demonstrated that greater subsurface drainage rates in snow dominated catchments in the Western US tended to increase spring sensitivity to warming and decrease summer streamflow sensitivity (Tague and Grant, 2009). We note that differences in SF response across drainage parameters are solely due to the effect of subsurface effective conductivity/drainage rates since all other factors, including topography and changes in snow accumulation and melt, are held constant across the warming scenarios (Fig. 7b). These differences in response of SF watershed as a function of drainage parameters highlight

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the importance of accounting for geologically based differences in drainage rates in addition to topographic differences. Further, the emergence of end-member parameters that are consistent with mappable geologic classifications points to an approach for accomplishing this in the face of limited stream gage data.

These findings have broad implications for the use of distributed hydrologic models as a means of predicting downscaled streamflow response to climate warming, as is becoming increasingly common (Hamlet and Lettenmaier, 1999; Payne et al., 2004; Christensen et al., 2004; VanRheenen et al., 2004; Wood et al., 2004). Our results show that if predictions are needed in basins where calibrations have not been explicitly conducted, great caution needs to be exercised if these uncalibrated basins reflect different geologies than those where calibrated parameters were derived. Furthermore, in basins with mixed lithologies, which are the norm for larger watersheds, calibrated parameters need to be developed across the full range of drainage efficiencies and cannot be confidently applied simply based on basin proximity.

6 Conclusions

The hydro-climatic setting in the McKenzie River watershed offers an illustrative example that may reflect other similar mountain systems, where spatial patterns of snow accumulation and melt are super-imposed on geologically mediated differences in subsurface drainage and storage. In these settings, modeling the spatial response of streamflow to predicted climate change requires disentangling the spatial interaction between the static differences in subsurface drainage properties and the dynamic transition between rain and snow. To estimate how these systems will respond to climate variability and change, process-based modeling must represent the natural physical processes controlling runoff and capture relevant spatial differences in climate inputs and soil/drainage parameters. For climate inputs, limited spatial coverage by meteorologic stations with long-term records leads to the use of interpolation schemes, such as PRISM, to account for spatial difference in climate inputs. Continued improvements

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in estimates of precipitation and temperature spatial-temporal patterns, both for retrospective and future analysis, are a critical research area. Limited spatial coverage of gaged streams to calibrate drainage parameters, however, is also an important factor and necessitates a strategy for drainage parameter transfer. In this paper, we demonstrate a successful drainage parameter transfer approach based on end-member parameter sets associated with mapped geologic classes. Streamflow estimation using this geologic end-member approach to transfer parameters was sufficient to capture historic climate variability for a set of watersheds that cross a range of scales from 1st to 4th order streams, including one watershed that comprised a mixture of geologic classes from both end-members. Model error using this geologic end-member approach to assign drainage parameters was also small relative to changes in seasonal streamflow patterns associated with simple warming scenarios. For watersheds with a mixture of geology, assigning uniform parameters results in substantial degradation in flow, but perhaps more importantly, leads to substantially different estimates of the impact of warming on flow seasonality. These results argue for the importance of accounting for drainage parameter heterogeneity and offer a method for doing so.

Our geologic end-member approach could be used to model the full distribution of hydrologic responses to climate warming within the McKenzie and potentially adapted for other areas of the mountainous Western US. The need for this type of multi-scale modeling and parameterization approach is particularly important in assessments of climate change impacts on aquatic habitat, where the spatial patterns and diversity of hydrologic response within river basins may be important drivers of habitat quality and sensitivity to environmental change.

While the McKenzie watershed incorporates sub-watersheds with sharply contrasting hydrogeological terrains, it is by no means unique. Similar differences in drainage efficiencies would be expected in watersheds drained by both karstic and non-karstic lithologies, deeply weathered versus unweathered intrusive or sedimentary bodies, or glaciated versus non-glaciated terrain. Parameterization schemes for hydrologic

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models along the lines that we have outlined here offer a useful means of characterizing and interpreting the hydrologic differences among these varied settings.

References

Barnett, T. P., Adam, J. C., and Lettenmaier, D. P.: Potential impacts of a warming climate on water availability in snow-dominated regions, Nature, 38, 303–309, 2005.

Baron, J. S., Hartman, M. D., Band, L. E., and Lammers, R. B.: Sensitivity of a high elevation Rocky Mountain watershed to altered climate and CO_2, Water Resour. Res., 36, 89–99, 2000.

Christensen, N. S., Wood, A. W., Voisin, N., Lettenmaier, D. P., and Palmer, R. N.: Effects of climate change on the hydrology and water resources of the Colorado River Basin, Climatic Change, 62, 337–363, 2004.

Daly, C., Neilsen, R. P., and Phillips, D. L.: A statistical-topographic model for mapping climatological precipitation over mountainous terrain, J. Appl. Meteorol., 33, 140–158, 1994.

Farley, K. A., Tague, C., and Grant, G.: Vulnerability of water supply from the Oregon Cascades to changing climate: Linking science to users and policy, Global Environ. Change, 21, 110–122, 2011.

Franz, J., Hogue, T. S., and Sorooshian, S.: Operational snow modeling: addressing the challenges of an energy balance model for National Weather Service forecasts, J. Hydrol., 360, 31–47, 2008.

Graves, D. and Change, H.: Hydrologic impacts of climate change in the Upper Clackamas River Basin, Oregon, USA, Clim. Res., 33, 143–157, 2007.

Hamlet, A. F. and Lettenmaier, D. P.: Effects of climate change on hydrology and water resources in the Columbia River Basin, J. Am. Water Resour. As., 35, 1597–1623, 1999.

Hay, E. and Clark, M. P.: Use of statistically and dynamically downscaled atmospheric model output for hydrologic simulations in three mountainous basins in the Western United States, J. Hydrol., 282, 56–75, 2003.

Hayhoe, K., Cayan, D., Field, C., Frumhoff, P., Maurer, E., Miller, N., Moser, S., Schneider, S., Cahill, K., Cleland, E., Dale, L., Drapek, R., Hanemann, R. M., Kalkstein, L., Lenihan, J., Lunch, C., Neilson, R., Sheridan, S., and Verville, J.: Emissions pathways, climate change, and impacts on California, Proc. Natl. Acad. Sci. USA, 101, 12422–12427, 2004.

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Hidalgo, H. G., Das, T., Dettinger, M. D., Cayan, D. R., Pierce, D. W., Barnett, T. P., Bala, G., Mirin, A., Wood, A. W., Bonfils, C., Santer, B. D., and Nozawa, T.: Detection and attribution of streamflow timing changes to climate change in the Western United States, J. Climate, 22, 3838–3855, 2009.

Jefferson, A., Grant, G., and Rose, T.: Influence of volcanic history on groundwater patterns on the west slope of the Oregon High Cascades, Water Resour. Res., 42, W12411, doi:10.1029/2005WR004812, 2006.

Jefferson, A., Nolin, A., Lewis, S., and Tague, C.: Hydrogeologic controls on streamflow sensitivity to climate variation, Hydrol. Process., 22, 4371–7385, 2008.

Jung, I. W. and Change, H.: Assessment of future runoff trends under multiple climate change scenarios in the Willamette River Basin, Oregon, USA, Hydrol. Process., 25, 257–278, 2010.

Knowles, N. and Cayan, D. R.: Potential effects of global warming on the Sacramento/San Joaquin watershed and the San Francisco estuary, Geophys. Res. Lett., 29, 1891–1894, 2002.

Knowles, N., Dettinger, M. D., and Cayan, D. R.: Trends in snowfall versus rainfall for the Western United States, J. Climate, 19, 4545–4559, 2006.

Mote, P. W. and Salathé Jr., E. P.: Future climate in the Pacific Northwest, Climatic Change, 102, 29–50, doi:10.1007/s10584-010-9848-z, 2010.

Nolin, A. and Daly, W. C.: Mapping at-risk snow in the Pacific Northwest, J. Hydrometeorol., 7, 164–1171, 2006.

Null, S. E., Viers, J. H., and Mount, J. F.: Hydrologic response and watershed sensitivity to climate warming in California's Sierra Nevada, PLoS ONE, 5, e9932, doi:10.1371/journal.pone.0009932, 2010.

Payne, J. T., Wood, A. W., Hamlet, A. F., Palmer, R. N., and Lettenmaier, D. P.: Mitigating the effects of climate change on the water resources of the Columbia River Basin, Climatic Change, 62, 233–256, 2004.

Perkins, R. M. and Jones, J. A.: Climate variability, snow, and physiographic controls on storm hydrographs in small forested basisn, Western Cascades, Oregon, Hydrol. Process., 22, 4949–4964, 2008.

Regonda, S. K., Rajagopalan, B., Clark, M., and Pitlick, J.: Seasonal cycle shifts in hydroclimatology over the Western United States, J. Climate, 18, 372–384, 2005.

HESSD
9, 8665–8700, 2012

Sherrod, D. R. and Smith, J. G.: Geologic map of upper Eocene to Holocene volcanic and related rocks of the Cascade Range, Oregon, US Geol. Surv. Geol. Invest. Ser. I-2569, 17 pp., Reston, Va., 2000.

Singh, V. P. and Woolhiser, D. A.: Mathematical modeling of watershed hydrology, J. Hydrol. Eng., 7, 270–292, doi:10.1061/(ASCE)1084-0699(2002)7:4(270), 2002.

Stewart, I. T., Cayan, D. R., and Dettinger, M. D.: Changes in snowmelt runoff timing in Western North America under a "business as usual" climate change scenario, Climatic Change, 62, 217–232, 2004.

Stewart, I. T., Cayan, D. R., and Dettinger, M. D.: Changes toward earlier streamflow timing across Western North America, J. Climate, 18, 1136–1155, 2005.

Tague, C. and Band, L.: RHESSys: Regional Hydro-ecologic simulation system: an object-oriented approach to spatially distributed modeling of carbon, water and nutrient cycling, Earth Interact., 8, 1–42, 2004.

Tague, C. L. and Grant, G.: A geological framework for interpreting the low flow regimes of Cascade streams, Willamette River Basin, Oregon, Water Resour. Res., 40, W04303, doi:10.1029/2003WR002629, 2004.

Tague, C. and Grant, G.: Groundwater dynamics mediate low flow response to global warming in snow-dominated alpine regions, Water Resour. Res., W07421, doi:10.1029/2008WR007179, 2009.

Tague, C., Farrell, M., Grant, G., Choate, J., and Jefferson, A.: Deep groundwater mediates streamflow response to climate warming in the Oregon Cascades, Climatic Change, 86, 189–210, 2008.

Thorndahl, S., Beven, K. J., Jensen, J. B., and Schaarup-Jensen, K.: Event based uncertainty assessment in urban drainage modelling, applying the GLUE methodology, J. Hydrol., 357, 421–437, 2008.

Troch, P. A., Carrillo, G. A., Heidbüchel, I., Rajagopal, S., Switanek, M., Volkmann, T. H. M., and Yaeger, M.: Dealing with landscape heterogeneity in watershed hydrology: a review of recent progress toward new hydrological theory, Geography Compass, 3, 375–392, doi:10.1111/j.1749-8198.2008.00186.x, 2009.

US Environmental Protection Agency: EPA Region 10 Guidance for EPA Project # 910-B-03-002, Pacific Northwest State and Tribal Temperature Water Quality Standards, Region 10 US EPA, Seattle, WA., 57 pp., 2003.

HESSD
9, 8665–8700, 2012

US Government: Streamflow Information for the Next Century: A Plan for the National Streamflow Information Program of the US Geological Survey, General Books LLC, 2011ISBN1234187809, 9781234187804, 20 pp., Reston, Va., 1999.

Van der Linden, S. and Woo, M. K.: Transferability of hydrological model parameters between basins in data-sparse areas, Subarctic Canada, J. Hydrol., 270, 182–194, 2003.

VanRheenen, N. T., Wood, A. W., Palmer, R. N., and Lettenmaier, D. P.: Potential implications of PCM climate change scenarios for California hydrology and water resources, Climatic Change, 62, 257–281, 2004.

Waichler, S. R, Wemple, B. C., and Wigmosta, M. S.: Simulation of water balance and forest treatment effects at the H. J. Andrews Experimental Forest, Hydrol. Process., 19, 3177–3199, 2005.

Wagener, T. and Wheater, H. S.: Parameter estimation and regionalization for continuous rainfall-runoff models including uncertainty, J. Hydrol. 320, 132–154. 2006.

Wood, A. W., Leung, L. R., Sridhar, V., and Lettenmaier, D. P.: Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs, Climatic Change, 62, 189–216, doi:10.1023/B:CLIM.0000013685.99609.9e, 2004.

Zierl, B., Bugmann, H., and Tague, C.: Evaluation of water and carbon fluxes in the ecohydrological model RHESSys, Hydrol. Process., 21, 3328–3339, 2006.

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Table 1. Watershed characteristics.

Watershed (WS)	Abbreviation	Drainage (km^2)	Elevation (m)	Geology
Budworm Creek	BUD	7.77 (54.5)	619–1626	WC
Lookout Creek	HJA	62.4	428–1620	WC
Mack Creek	MACK	5.8	758–1610	WC
Watershed 2	W2	0.60	548–1070	WC
Watershed 8	W8	0.22	993–1170	WC
Clearlake	CLR	239.3	924–2019	HC
Horse Creek	HORSE	387.5	439–3152	HC
Southfork	SF	538.7	530–2044	36 % WC; 64 % HC

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Table 2. Number of acceptable parameters sets for each watershed.

WS	Initial Criteria (NSElog > 0.5)	Stringent Criteria (NSElog > 0.8)
CLR	17 (3 %)	0
HORSE	11 (2 %)	0
BUD	266 (44 %)	20 (3 %)
HJA	431 (72 %)	185 (31 %)
MACK	404 (67 %)	152 (25 %)
W2	327 (55 %)	126 (21 %)
W8	376 (63 %)	111 (19 %)

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Table 3. Example of an acceptable parameter set across common geologic watersheds.

WS	*m*	*K*	pa	po	gw1	gw2
CLR	5.1	34	0.9	1.6	0.3	0.6
HORSE	5.1	34	0.9	1.6	0.3	0.6
BUD	0.8	58	1.8	1.1	0	0
HJA	0.8	58	1.8	1.1	0	0
MACK	0.8	58	1.8	1.1	0	0
W8	0.8	58	1.8	1.1	0	0
W2	1.8	249	1.8	1.3	0.2	0.6

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Table 4. Model performance across four chosen parameters.

WS	Calibration (WY 1999–2000)		Evaluation (longest period)			Evaluation (WY 1980–1986)	
	LogNSE	NSE	LogNSE	NSE	Eval. Period	LogNSE	NSE
CLR	0.51–0.67	0.30–0.68	0.61–0.68	0.55–0.56	WY 70-06	0.54–0.62	0.50–0.53
HORSE	0.50–0.62	0.46–0.65	0.52–0.59	0.40–0.48	WY 62-69	NA	NA
BUD	0.80–0.83	0.62–0.68	0.68–0.75	0.40–0.45	WY 79-86	0.67–0.74	0.40–0.44
HJA	0.82–0.91	0.72–0.82	0.68–0.82	0.47–0.60	WY 58-05	0.70–0.80	0.49–0.62
MACK	0.85–0.91	0.60–0.70	0.68–0.76	0.41–0.49	WY 80-06	0.56–0.69	0.40–0.53
W2	0.83–0.91	0.51–0.61	0.69–0.75	0.36–0.44	WY 58-06	0.66–0.74	0.31–0.43
W8	0.88–0.89	0.60–0.66	0.74–0.75	0.35–0.37	WY 64-05	0.69–0.72	0.39–0.46
SF	NA	NA	0.75–0.80	0.58–0.66	WY 58-88	0.68–0.75	0.59–0.69

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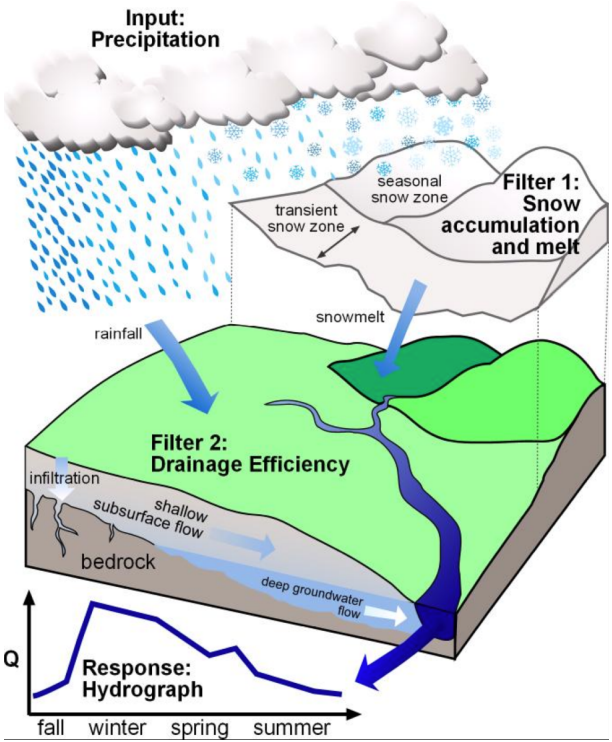

Fig. 1. Landscape responses to precipitation inputs – as a series of filters (Tague and Grant, 2009).

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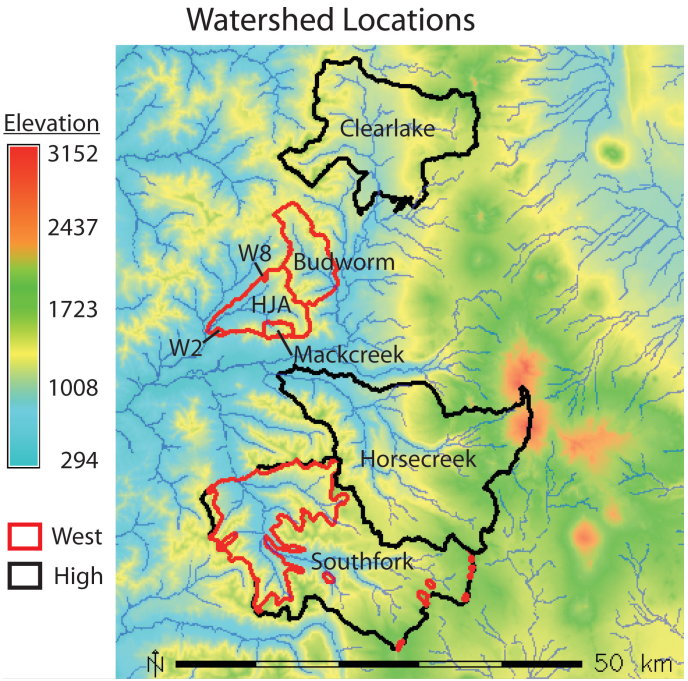

Fig. 2. Map showing study watersheds (listed in Table 1) and geologic classification.

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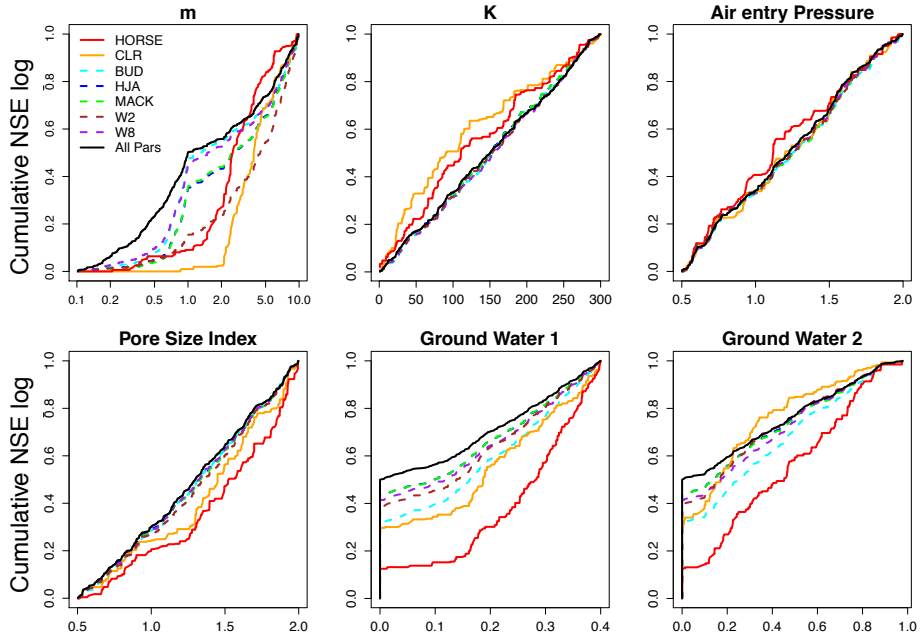

Fig. 3. Cumulative distribution of performance across parameter sets. Solid black line shows the original parameter distribution; colored lines show distribution of performance by parameter value for each watershed. Departures from the black line show preference for particular parameter values.

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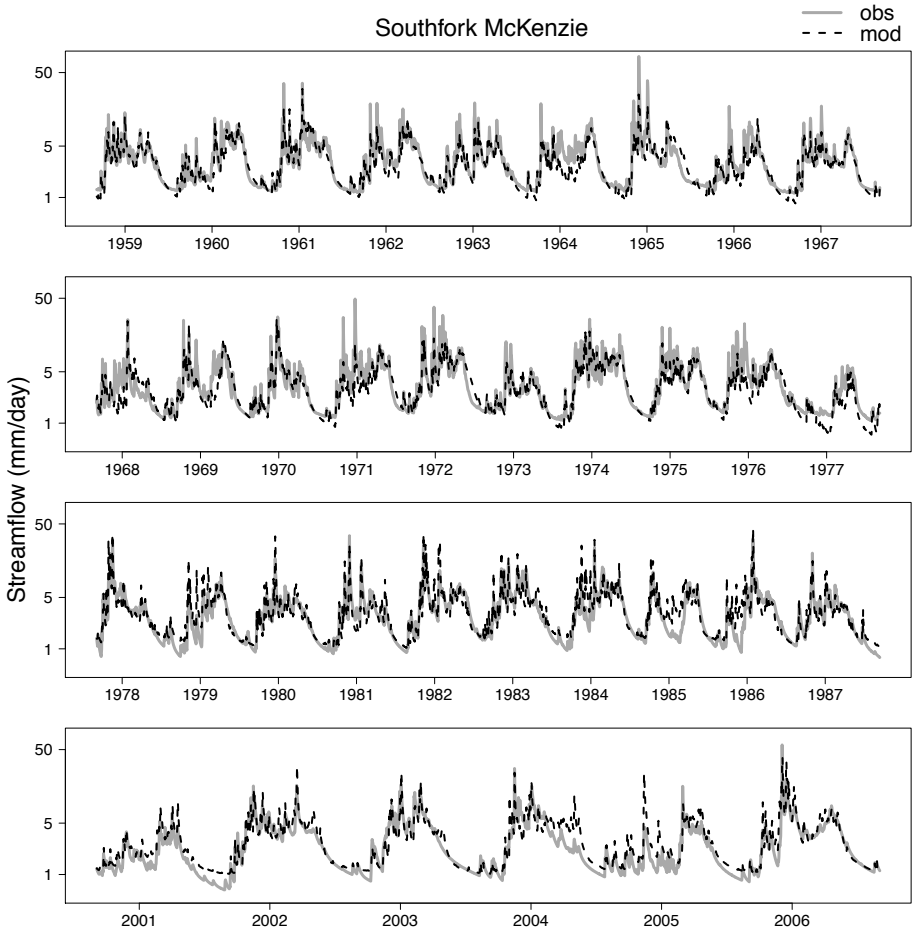

Fig. 4. Southfork watershed streamflow, modeled and observed. Modeled streamflows are generated using geologic end-members to assign soil drainage parameters.

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Parameterizing sub-surface drainage with geology

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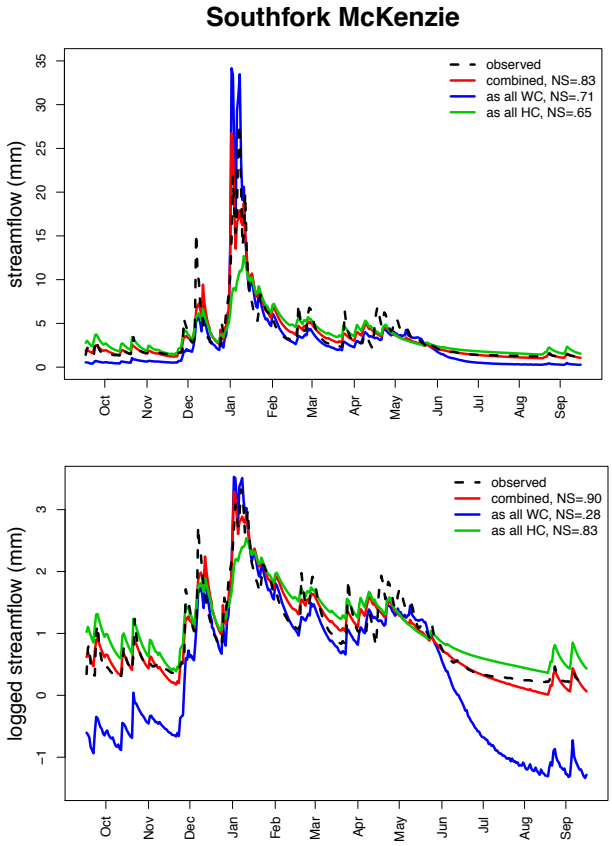

Fig. 5. Observed and modeled daily **(a)** streamflow and **(b)** log-transformed streamflow for Southfork McKenzie. Modeled streamflow estimates are shown for three parameter-transfer strategies including using only WC end-member parameters, only HC end-member parameters and combined strategy where parameters are varied spatially according to HC/WC geologic classification within the Southfork watershed.

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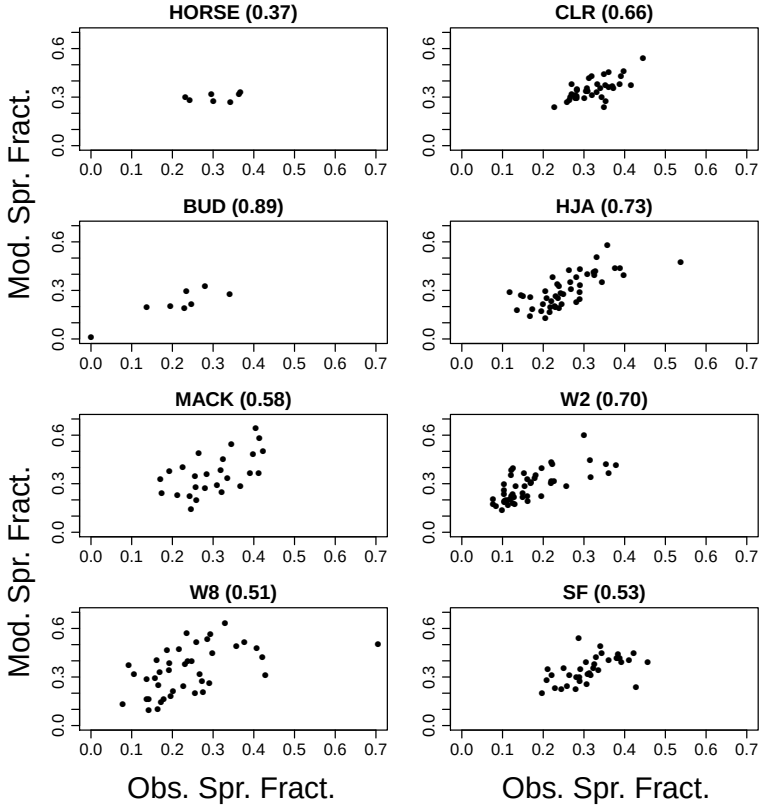

Fig. 6. Correlation between observed and modeled spring fraction of annual flow. Values in brackets are Pearson Correlation Coefficient – all were significant at 99 % confidence. Results are shown for a single acceptable parameter set and for all years with observed/modeled streamflow (available water years for each watershed are listed in evaluation column of Table 4).

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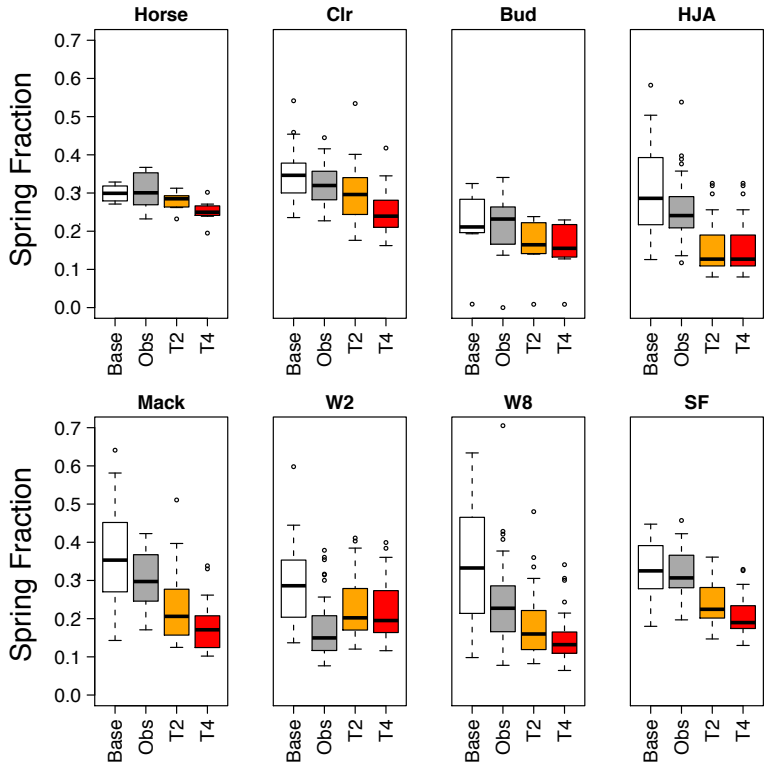

Fig. 7a. Variation in spring fraction of annual flow for modeled (white) and observed (grey) with historic climate (WY) and modeled results for a 2˚C (orange) and 4˚C (red) warming scenario. Results are shown for a single acceptable parameter set and for all years with observed/modeled streamflow (available water years for each watershed are listed in evaluation column of Table 4).

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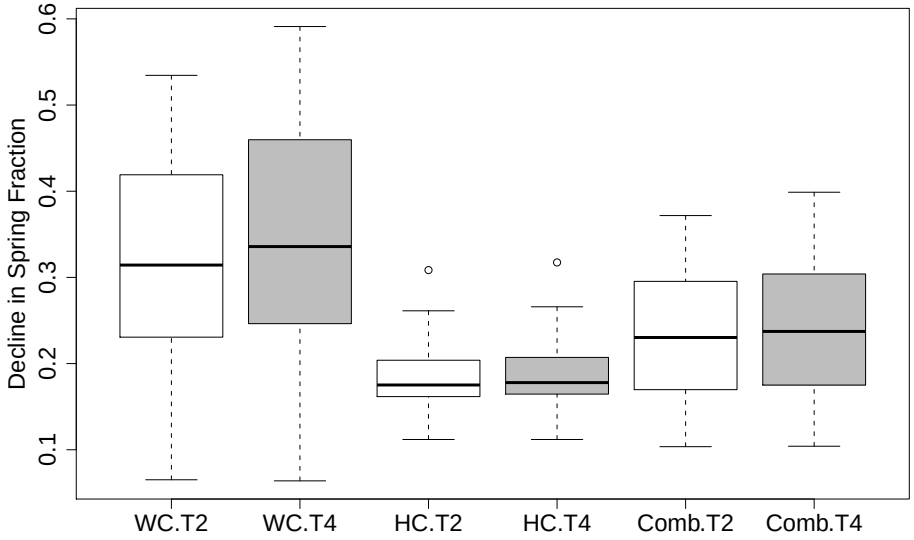

Fig. 7b. Change in modeled spring fraction of annual flow for 2°C (white) and 4°C (grey) warming scenarios in SF run as all WC, as all HC, and SF comprised of both HC and WC.

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Coupling Snowpack and Groundwater Dynamics to Interpret Historical Streamflow Trends in the Western United States

Journal:	*Hydrological Processes*
Manuscript ID:	HYP-12-0310.R1
Wiley - Manuscript type:	Special Issue Paper
Date Submitted by the Author:	n/a
Complete List of Authors:	Safeeq, Mohammad; Oregon State University, Geosciences Grant, Gordon; USDA Forest Service, PNW Research Station Lewis, Sarah; Oregon State University, College of Earth, Ocean, and Atmospheric Sciences Tague, Christina; University of California, Bren School of Environmental Science and Management
Keywords:	streamflow trend, hydrologic processes, groundwater processes, Climate warming

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Coupling Snowpack and Groundwater Dynamics to Interpret Historical Streamflow Trends in the Western United States

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Hydrologic Processes

Abstract

A key challenge for resource and land managers is predicting the consequences of climate warming on streamflow and water resources. Over the last century in the western US significant reductions in snowpack and earlier snowmelt have led to an increase in the fraction of annual streamflow during winter, and a decline in the summer. Previous work has identified elevation as it relates to snowpack dynamics as the primary control on streamflow sensitivity to warming. But along with changes in the timing of snowpack accumulation and melt, summer streamflows are also sensitive to intrinsic, geologically-mediated differences in the efficiency of landscapes in transforming recharge (either as rain or snow) into discharge; we term this latter factor drainage efficiency. Here we explore the conjunction of drainage efficiency and snowpack dynamics in interpreting retrospective trends in summer streamflow during 1950-2010 using daily streamflow from 81 watersheds across the western US. The recession constant (k) and fraction of precipitation falling as snow (S_f) were used as metrics of deep groundwater and overall precipitation regime (rain and/or snow), respectively. This conjunctive analysis indicates that summer streamflows in watersheds that drain slowly from deep groundwater and receive precipitation as snow are most sensitive to climate warming. During the spring, however, watersheds that drain rapidly and receive precipitation as snow are most sensitive to climate warming. Our results indicate that not all trends in western US are associated with changes in snowpack dynamics; we observe declining streamflow in late fall and winter in rain-dominated watersheds as well. These empirical findings support both theory and hydrologic modeling, and have implications for how streamflow sensitivity to warming is interpreted across broad regions.

Introduction

Changes in streamflow timing and magnitude have been a key research area over the past few decades. Declines in streamflow magnitude (Lins and Slack, 1999; Luce and Holden, 2009), altered flood risk (Hamlet and Lettenmaier, 2007), and earlier centroid of annual streamflow (Stewart, *et al.*, 2005) have been reported for the western US. The majority of these changes have been attributed to significant reductions in snowpack and earlier snowmelt, which in turn have been interpreted as primarily due to anthropogenic climate warming (Hidalgo, *et al.*, 2009; Barnett, *et al.*, 2008). Continuing warming trends in mid-latitude areas (Adam, *et al.*, 2009; IPCC, 2007) will only intensify the focus on changes in snow accumulation and melt rate as key drivers of future impacts on the hydrologic cycle (Nijssen, *et al.*, 2001), particularly in regions with "warm" snow packs, i.e., snow accumulation occurring near 0 ^{o}C, such as the US Pacific Northwest (Nolin and Daly, 2006).

Most studies of historical changes in western US streamflow have shown an overall decline in summer flow, while the volume of annual streamflow has not changed much over the past 50 years. Warming-induced changes in snow accumulation and melt in lower elevation watersheds are interpreted as changing the inter-seasonal distribution of streamflow. Stewart et al. (2005), for example, showed a strong link between the start of spring snowmelt and elevation, In particular, the fraction of annual streamflow during winter has increased, while the summer fraction has decreased (Stewart, *et al.*, 2005; Regonda, *et al.*, 2005; Aguado, *et al.*, 1992; Dettinger and Cayan, 1995). Using quantile regression, Luce and Holden (2009) showed asymmetric changes in the distribution of annual flow, with greatest change in the lower

quantile. Ragonda et al. (2005) showed that spring season peak flows occurred earlier in the year in lower elevation watersheds, which was reflected in higher overall winter flow and lower flows during summer.

However, changes in snow dynamics are not the only driver of changes in streamflow. There are four primary filters (both climatic and non-climatic) that control the shape of the hydrograph and its response to change as illustrated using a conceptual annual hydrograph (Figure 1). The annual peak of the hydrograph (Figure 1A) is primarily dependent on the amount of annual precipitation (wet year vs. dry year), whereas timing and type of precipitation (rain vs. snow) determine the timing of flow during the year (Figure 1B). The rate of hydrograph recession, which primarily depends on subsurface geology, controls both the portioning of subsurface water into shallow or deep pathways, and affects the rate at which these compartments contribute to streamflow (Figure 1C). Factors such as aquifer permeability (as influenced by rock and rock unit porosity and fractures) and aquifer slope are the dominant means by which geology influences the recession characteristics of the hydrograph. Finally, changes in loss of water to the atmosphere in the form of evapotranspiration can also affect (increase or decrease) the hydrograph, mainly during the spring and summer growing season (Figure 1D). These four filters interact in a complex fashion to produce the hydrograph; climate affects all of these factors except the geologically mediated recession rate. The convoluted effect of these filters on hydrograph shape under different runoff regimes can be simulated using a hydrologic model (e.g. Déry*, et al.*, 2009).

Recent work highlights the role of underlying geology in controlling hydrologic responses to climate change (Tague and Grant, 2009; Tague*, et al.*, 2008; Arnell, 1992; Mayer and Naman, 2011; Tague and Grant, 2004). Tague and Grant (2009) propose a simple conceptual model relating sensitivity of summer streamflow to two factors: the timing of the snowmelt peak relative to late season flows, and drainage efficiency, defined as the geologically mediated rate at which recharge, either as rain or snow, is transformed into discharge. They show that, in principle, the magnitude of changes in late season streamflow will be more sensitive to later as opposed to earlier melting snowpack, and more sensitive to slower as opposed to faster draining landscapes. Climate warming can potentially affect the timing of snowpack melting directly, but does not alter the intrinsic drainage properties of the landscape. Interpreting sensitivity at a broad regional scale, however, requires that both factors be considered.

Building on the conceptual framework of Tague and Grant (2009), in this paper we develop an empirical approach to examining historical trends in streamflow that incorporates both snowpack dynamics and drainage efficiency. Using long-term observed streamflow data from 81 unregulated watersheds distributed across a wide range of precipitation regimes (rain, snow, mixed) and geological settings (i.e. drainage efficiencies) in the western US, we extract key precipitation- and streamflow-based metrics, and use these to classify watersheds with respect to snowpack and drainage efficiencies. This classification then allows us to re-interpret historical trends in light of the sensitivity relationships posited by Tague and Grant (2009). The result of this analysis is a more robust means of extending forecasts of climate-driven changes in streamflow regime to watersheds without long-term observations, based on their geologies and geographic settings. While we utilize streamflow records from the western US to test these concepts, in principal this approach should work in most temperate and Mediterranean settings with strongly seasonal precipitation regimes.

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Geography, Data, and Methods

Geographic area

We focused our analysis on the western US, which is characterized by a Mediterranean climate with warm dry summers and cool wet winters, and with significant precipitation falling as snow at higher elevations. In mountainous regions the seasonal distribution of streamflow is predominantly derived from snow, making it very sensitive to changes in temperature, as compared to elsewhere in the USA (Adam*, et al.*, 2009; Nolin and Daly, 2006). Catchment characteristics such as aquifer permeability and drainage efficiency differ markedly across the western US. Streamflow recedes rapidly in watersheds with little or no spring snowmelt and limited groundwater storage (e.g. coast ranges of Washington, Oregon, and northern California) resulting in high winter peaks and prolonged summer low flows. Higher elevation watersheds that receive a mix of rain and snow without much groundwater storage, such as the western Cascades of Oregon and Washington, have high winter flows, an early to mid-spring snowmelt peak and low summer flows. High alpine areas with little groundwater storage, such as the Sierra Nevada of California, have late spring and early summer snowmelt peaks that recede rapidly. Groundwater-dominated areas (e.g. the high Cascades of southern Washington, Oregon, and northern California) are also dominated by snowmelt but show a much more uniform flow regime, with higher summer baseflows, slower recession rates, and significantly lower winter peak flows.

Streamflow Data

We used the high quality daily streamflow data from 81 Model Parameter Estimation Experiment (MOPEX) gages (Schaake*, et al.*, 2001) located in the western US with records extending from 1949- 2010. MOPEX watersheds are a subset of the Hydroclimatic Data Network (HCDN) gages (Slack*, et al.*, 1993), and a data set compiled by Wallis et al. (Wallis*, et al.*, 1991). These watersheds are unregulated and span a wide variety of climate regimes (Duan*, et al.*, 2006). The drainage areas of watersheds examined ranged between 23 and 36599 km^2 with a median of 546 km^2 (Appendix A1).

Watershed classification framework

Based on the conceptual framework posited by Tague and Grant (2009), we developed a watershed classification scheme for interpreting streamflow sensitivity to climate warming, using the precipitation regime and drainage efficiency that controls the magnitude, timing, and delivery of water to stream networks. This technique required developing metrics sensitive to precipitation regime and drainage efficiency.

Metrics for Precipitation Regime

We used concurrent (1950-2010) 1/16 degree spatial resolution and gridded daily temperature and precipitation data for the selected study domain to characterize the precipitation regime over each watershed. The temperature and precipitation data used in this study were derived by Livneh et al. (2012) from the National Oceanic and Atmospheric Administration (NOAA)

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Cooperative Observer (Coop) stations following the gridding technique of Hamlet and Lettenmaier (2005) and are available at a 1/16 degree resolution over the CONUS domain for the period 1915–2010. Using an average temperature threshold of 0°C, daily precipitation at each grid cell was classified as rain or snow (Jefferson, 2011). Although the temperature threshold between precipitation falling as rain versus snow varies across the study domain, 0°C was chosen to approximate the broad regional patterns of the dominant type (rain or snow) of precipitation. For each watershed, the spatially averaged snow fraction S_f (% of precipitation falling as snow) was estimated using all the grid cells within the watershed boundary. Based on the average snow fraction over 1950-2010, watersheds were classified into three groups: (i) rain dominated (S_f <10%), (ii) mixture of rain and snow (10 % ≤ S_f < 45%), and (iii) snow dominated (S_f ≥ 45 %). Since our classification of watersheds based on the precipitation regime is dependent on a S_f threshold that includes the confounding effect of recent warming, we tested our classification scheme by reclassifying the watersheds based on much longer (1915-2010) temperature and precipitation datasets. If recent warming had any impact on our classification scheme, then we would expect more watersheds being classified as snow dominated compared to a mixture of rain and snow in the longer dataset. The comparison showed, however, that only three watersheds changed from snow dominated to a mixture of rain and snow, and only one watershed changed from a mixture of rain and snow to snow dominated, indicating that our classification is not much affected by recent warming.

Metrics for Drainage Efficiency

We used the baseflow recession constant for characterizing the efficiency with which recharge becomes discharge, which is primarily a function of the watershed hydraulic conductivity and soil porosity as well as the hydraulic gradient (Sujono*, et al.*, 2004). Following a linear reservoir model, hydrograph recession after recharge input (as snowmelt or rain) is given by:

$$Q_t = Q_o e^{-kt} \qquad [1]$$

where Q_t is streamflow at time, t (in days), Q_o is streamflow at the beginning of the recession period, and k is a baseflow recession constant. We used k as a proxy for drainage efficiency, since it reflects the rate at which water moves through the subsurface, as well as the rate of recharge. There are a variety of approaches for determining k, including plotting individual recession segments on a semi-logarithmic plotting graph, and developing a master recession curve (Tallaksen, 1995). The recession constant k derived from individual segments varies with season and length of recession following a recharge event and may not represent the characteristic recession (Tallaksen, 1995). For this reason, we adopted the master recession curve procedure, which represents average watershed condition by combining the individual segments. It is important to recognize that k is not completely independent of recharge, particularly from snowmelt. We took steps, however, to segregate the effect of drainage efficiency versus recharge, as discussed below.

For the purpose of this analysis we constructed the master recession curves for each watershed using the following approach to determine the watershed representative k:

1. We first identified all individual recession segments with length >15 days. We considered these longer recessional segments to ensure the beginning of baseflow recession following recharge events.

2. The beginning of recession (inflection point) was identified following the method of Arnold et al. (1995) using drainage area.
3. To minimize the effect of snowmelt recharge on k, recession segments identified between the onset of the snowmelt-derived streamflow pulse and August 15 were excluded. Days of snowmelt pulse onset were determined following the method of Cayan et al. (2001).
4. The master recession curve was constructed using the adapted matching strip method (Posavec*, et al.*, 2006), and k was determined as the slope of the linear regression between log-transformed discharge and recession length.

We discretized watersheds into two classes as: "low k" watersheds with $k < 0.065$, and "high k" watersheds with $k \geq 0.065$. We used the 0.065 threshold for k to broadly distinguish between these two major stream types. The low k watersheds represent groundwater dominated slow draining systems whereas high k watersheds represent shallow subsurface flow dominated fast draining systems. We acknowledge that differences in k could be caused by a variety of landscape characteristics (e.g. hydraulic gradient, relief, and drainage area) other than deep versus shallow subsurface flow systems. At the scale of the western US, however, we found no significant correlation between k and drainage area (Spearman's r = -0.11, p=0.33), and between k and relief (Spearman's r = -0.13, p=0.26). To further test our interpretation of k as primarily a metric of geologically mediated drainage efficiency, we correlated k with aquifer permeability for 58 (of which 13 included in this study) Oregon watersheds. The aquifer permeability data for Oregon (provided by P. J. Wigington Jr. at US-EPA, Corvallis, OR) was developed based on the correspondence between lithology (Walker *et al.*, 2003) and measured values of aquifer unit hydraulic conductivity (Gonthier, 1984; McFarland, 1983). We found a significant negative correlation between k and aquifer permeability (Spearman's r = -0.35, p=0.007) but no correlation between k and drainage area (Spearman's r = -0.03, p=0.81). A similar analysis from the larger population of 81 watersheds used in this study was not possible due to a lack of hydrologically relevant geologic classification for the entire western US. Nonetheless, the k-aquifer permeability relationship in Oregon provides support for using k as a metric of geologically mediated drainage efficiency. A summary of means and corresponding standard deviations of k under different precipitation regimes (i.e. rain, mixture of rain and snow, and snow) are presented in Table 1.

Streamflow indices

Our evaluation of historical streamflow trends focused on variation over time of the following two indices:

1. **Total streamflow (monthly, seasonal, and annual)**: Anticipated earlier snowmelt and change in precipitation type will have a non-uniform effect on monthly and seasonal streamflow. To explore how hydro-geologic differences among the watersheds might influence changes in streamflow on varying time scales, we analyzed monthly, seasonal, and annual total streamflow for trends in individual watersheds. Seasons were defined on a water year basis as fall (OND), winter (JFM), spring (AMJ), and summer (JAS).
2. **Summer runoff ratio:** We calculated the summer (JAS) runoff ratio for each watershed after dividing the total summer streamflow by the annual precipitation derived from PRISM data (Daly et al., 2008). The average annual precipitation over a watershed was calculated from watershed averaged monthly precipitation. Trends for each watershed were calculated on the time series of the summer runoff ratio. For this index, we also

calculated trends on an average time series of mean summer runoff ratio derived from *n* watersheds within each of the six precipitation regime and *k* classes.

Secular Trend Detection

Trends over time in the streamflow indices were estimated by the nonparametric Mann–Kendall (MK) test (Kendall, 1975; Mann, 1945) and Sen's method (Sen, 1968). The MK test determines whether a trend is increasing or decreasing, and estimates the significance of the trend, while Sen's method quantifies the magnitude of the trend. A nonparametric Kruskal-Wallis multiple comparisons test was used to test for group differences in the monthly, seasonal, and water year trends by hydro-geologic regime type. A *p*-value of 0.05 for the Kruskal-Wallis test means that the trends from at least one group of watersheds are significantly different from the trends of the other watershed types.

Results

Our analysis is directed at identifying time trends in key streamflow indices in relation to underlying climatic and geologic controls. Ideally, such an analysis would clearly separate the effects of climate from geology in streamflow generation. In reality, both climate and geology are closely coupled in the streamflow signal; the hydrograph represents a complex convolution of both factors and teasing them apart is challenging. More specifically, S_f is a climate metric, reflecting the timing of precipitation input and recharge. As noted previously, *k* is primarily a function of watershed drainage characteristics, particularly those related to groundwater (i.e., porosity, hydraulic conductivity, hydraulic gradient), but will also be influenced to a lesser extent by the timing and magnitude of recharge (particularly snowmelt). We have tried to minimize this effect by calculating *k* for time periods when recharge for snowmelt and rainfall are at a minimum. Therefore in our analysis of results we interpret S_f as reflecting the climatic regime (and therefore sensitive to warming effects) while *k* primarily reflects the underlying geology of the watershed.

Generalized hydrographs:

The interaction between climate and geology as captured by our watershed classification framework is illuminated by a comparison of average daily flows (normalized by precipitation and watershed area) across watersheds from different climatic and geologic settings (Figures 2&3). Low *k*-rain dominated (LR) watersheds are mainly located along the Southern CA coast, whereas; high *k*-rain dominated (HR) watersheds are located along the OR and southern WA coast. Both, LR and HR watersheds show single-peaked hydrographs during the fall and winter seasons. Despite the long recession in LR and HR watersheds, streamflow during late summer is slightly higher in LR watersheds. In contrast, low *k*-mixture of rain and snow (LM) and high *k*-mixture of rain and snow (HM) watersheds are distributed throughout the study domain and show dual-peaked hydrographs. Streamflow during summer and early fall is much higher compared to LR and HR watersheds, which can be attributed to a snowmelt peak occurring later in the year. Similar to LM and HM, low *k*-snow (LS) and high *k*- snow (HS) watersheds are also spread across the study domain and show dual-peaked hydrographs. The first peak resulting from fall and winter rain is smaller than in LM and HM watersheds. Hydrologic characteristics of study watersheds grouped in terms of S_f and *k* are summarized in Table 1. Mean annual streamflow is independent of hydro-geologic regime and depends primarily on annual

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precipitation. However, percentage of annual streamflow occurring in summer is higher in low *k* (groundwater dominated) watersheds and increases with increasing S_f. Absolute summer flow is highest in watersheds with mixtures of rain and snow.

Predicting summer streamflow sensitivity from watershed classification

Combining our watershed classification scheme with the response surface derived from the conceptual model developed by Tague and Grant (2009) allows us to make first-order predictions of sensitivities of late summer (August 1st) streamflow depending on the hydro-geologic regime of watersheds. Following Tague and Grant (2009), we defined sensitivity as the change in August 1st streamflow to a change in the timing of recharge or a unit change in the magnitude of recharge. Among the different hydro-geologic regimes, August 1st streamflow in LS and LM watersheds is most sensitive to unit changes in the magnitude and an earlier shift (two weeks) in the timing of recharge (Figure 4). Under a similar precipitation regime (i.e. snow), watersheds show varying levels of sensitivity depending on *k*. Timing of snowmelt in LS watersheds are quite similar except Big Rock Creek, CA (USGS 10263500; Appendix A1), but summer streamflows show different levels of sensitivity to inter-annual variation in timing due to differences in *k*. On the other hand, LM watersheds have a similar range of *k* values as LS watersheds, but show a wider range of sensitivities due to varying timing of snowmelt. Although timing of snowmelt in LS and HS watersheds are similar, higher *k* for HS watersheds makes them less sensitive.

Historical streamflow trends in relation to watershed classification

Monthly Streamflow

Trends in monthly streamflow as a function of precipitation regime (rain, mixture of rain and snow, and snow) and drainage efficiency (*k)* reveal the interaction between these two controlling factors (Figure 5). In the low *k*-rain (LR) dominated watersheds, median trends in monthly streamflow are mostly positive, except for a small decline during the months of December and January (Table 2). Increases in August and October streamflow are statistically significant (p<0.10) in 40% and 60% of the LR watersheds, respectively. The greatest absolute streamflow increases in LR watersheds are during the months of February and March. In contrast, low *k*-mixture of rain and snow (LM) dominated watersheds show an overall negative trend in monthly streamflow except for March during which the trend is significantly (p<0.10) positive in 25% of the watersheds. Similarly, low *k*- snow (LS) dominated watersheds show an overall negative trend in monthly streamflow except March and April during which the trend is positive. Both the magnitude and timing of greatest streamflow decline varies between these two (LM and LS) watershed types. In LM watersheds the greatest decline is occurring during February in the winter and all months during the spring, whereas LS watersheds show the largest streamflow decline in May, June, July and August. These results indicate that both timing and magnitude of streamflow decline under a diminishing snowpack depend on the precipitation regime. Watersheds that receive precipitation mostly in the form of snow will show the greatest impact of warming during the late spring and early summer. Consistent with interpretations offered by Stewart et al. (2005), the increase in streamflow during March in LM watersheds and during March and April in LS watersheds can be attributed to decreasing S_f (more rain instead of snow) and earlier snowmelt.

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Unlike the low-*k* (groundwater dominated) watersheds, high-*k* watersheds (except high *k*-snow watersheds) show much larger declines in monthly streamflow during fall and winter months (Table 2; Figure 5). The high *k*-rain (HR) watersheds show large declines between October and April with >75% watersheds showing significant (p<0.10) trend in October and February. The most notable change has been in February (97 mm or 44%). These HR watersheds also show slightly larger streamflow increases between May and July compared to the corresponding LR watersheds. The mean monthly streamflow declines in high *k*-mixture of rain and snow (HM) watersheds are slightly greater compared to LM watersheds. These differences are large (nearly three-fold) in October and December. Additionally, HM watersheds show moderate increases in streamflow during January and much larger increases (nearly four-fold) in March. In high *k*-snow (HS) watersheds the most notable streamflow declines are in June (48 mm or 28%) which is slightly larger (in absolute terms) compared to declines in June streamflow in LS watersheds. At least 50% of the LS and HS watersheds showed a significant (p<0.10) trend. Similar to HM watersheds, increases in March and April streamflow in HS watersheds are large compared to corresponding LS watersheds.

Monthly streamflow trends in rain dominated watersheds (both LR and HR) are generally consistent with trends observed in the monthly precipitation data (Figure 6). In HR watersheds the most notable declines in January (71 mm) and February (97 mm) streamflow are in agreement with the greatest declines in precipitation (74 mm in January and 88 mm in February). In all LR watersheds, however, the effect of significant (p<0.10) increasing precipitation during February does not coincide with the month of largest streamflow increase. This can be attributed to delayed streamflow response to precipitation in groundwater dominated (low-*k*) watersheds. The large increase in March streamflow in LM, HM, LS, and HS watersheds does not correspond with in large decreasing trends in winter precipitation (65% of the studied watersheds showed decline in February precipitation). Hence these trends can be attributed to changes in the type of precipitation (more rain instead of snow), consistent with a climate warming interpretation.

Historical trends as expressed as changes in the magnitude and timing of monthly streamflow are different for each of our six groups of watersheds (Figure 5). First, there is a greater change in late summer streamflow in slow draining (low-*k*) LM and LS watersheds in contrast to the more rapidly draining (high-*k*) HM and HS watersheds. We assume that timing of recharge in HS and LS is similar; therefore the difference in magnitude of decline is primarily due to the effect of drainage efficiency. In slow draining (low-*k*) watersheds the effect of a change in timing and magnitude of recharge gets delayed and attenuated, whereas the response to similar changes in recharge timing and magnitude in rapidly draining (high-*k*) watersheds will be almost immediately expressed in the hydrograph. This pattern is consistent with the results shown using the response surface from the conceptual model (Figure 4) predicting greater changes in August 1st streamflow for LS watersheds.

Monthly changes in streamflow are not limited to the summer season. The largest absolute change in historical streamflow patterns is the decline in winter streamflow in HR watersheds, a decline that is not observed in LR watersheds (Figure 5). Two factors may be responsible for these results. First, the sample size for LR watersheds is small (n = 5), and potentially limits interpretation. A more important factor, however, is the clear decline in precipitation in HR watersheds as compared with LR watersheds (Figure 6). This re-emphasizes the point that all of

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the potential controls on hydrograph shape have to be taken into account in interpreting historical trends (Figure 1).

Seasonal Streamflow

To accentuate seasonal patterns, we compare trends in seasonal streamflow for each group of watersheds and interpret these results in light of changing precipitation regimes among other factors (Table 2). Looking at seasonal trends reveals patterns that are more easily interpreted with respect to underlying physical mechanisms than monthly totals. The LR watersheds show a trend of increasing streamflow during all seasons with the most notable change in winter (+20 mm). However, this streamflow increase is non-significant ($p > 0.10$) in all LR watersheds and only accounts for 20% of the total precipitation increase (Table 3). Although spring season streamflow shows a small upward trend (+2.5 mm), spring precipitation has declined by 6 mm. In contrast, spring precipitation in LM, HR, and HM watersheds has increased between 5 to 37 mm whereas spring streamflow in these watersheds shows a negative trend (-51 to -62 mm) except HR watersheds which showed no change. These increasing trends in spring precipitation and decreasing significant ($p < 0.10$ in at least 50% of the watersheds) trends in spring streamflow in LM and HM watersheds can be attributed to reductions in snowpack for these mixed precipitation type watersheds. For the HR watersheds, the underlying mechanisms that lead to no change in spring streamflow in response to increased precipitation are less clear. Since precipitation in HR watersheds declines by 36 mm in summer to 150 mm in winter, it may be that the effect of increased spring precipitation is negated by the water deficit caused by precipitation decline during the preceding seasons. Snow-dominated (LS and HS) watersheds show a moderate increase in winter streamflow despite the largest (90 mm in LS and 43 mm in HS) decline in winter precipitation among all seasons. Also the decline in spring (60-106 mm) and summer (16-35 mm) season streamflow is much higher compared to the mostly non-significant decline in precipitation (<4 mm in spring and 8-24 mm in summer). Reduction in snowpack and earlier snowmelt under a warmer climate is responsible for nearly all the trends during the spring in snow and mixture of rain and snow dominated watersheds. As a result of more winter rain instead of snow and earlier snowmelt, winter runoff ratio has increased in almost all watersheds (Figure 8), except HR which showed decline as a result of large precipitation decline (Table 3). LS and HS watersheds show greatest increase in winter runoff ratio as well as greatest decrease in runoff ratio during the summer.

The effect of geologic differences among watersheds is most evident in trends in summer runoff ratios (Q_{summer}/P_{annual}). All watersheds with a precipitation regime dominated by a mixture of rain and snow and only snow showed decreasing trends in summer runoff ratios, with the greater declines in slow draining (low-*k*) watersheds (Figure 7). Declines in summer runoff ratio in snow-dominated watersheds are slightly larger than in watersheds with precipitation regimes a mixture of rain and snow. There are no discernible trends in summer runoff ratio trends in rain-dominated watersheds. Trends in summer runoff ratio for individual watersheds are consistent with the aggregated pattern, with greatest median declines in LS watersheds (-3.8×10^{-3} /decade), which is nearly two fold higher than the HS watersheds ((-1.6×10^{-3} /decade). Similarly median trends in LM watersheds (-1.8×10^{-3} /decade) were higher than those in HM watersheds (-1.2×10^{-3} /decade). Differences in trends among the six different watershed types are statistically significant ($p<0.001$).

Annual Streamflow

On an annual basis, streamflow in LR watersheds increased by 38 mm in response to a 54 mm increase in annual precipitation. In the remaining watersheds, annual streamflow declined, and this decline diminishes in moving from rain- to snow-dominated watersheds. Decreasing trends were statistically significant ($p < 0.10$) in 44-50% of the watersheds. Although the decline in annual streamflow under high-k watersheds are higher, the Kruskal-Wallis test showed no significant difference ($p = 0.49$) between the six different watershed types. Similar statistical tests on the magnitude of trends between low-k and high-k watersheds, ignoring the type of precipitation, showed no significant difference ($p = 0.13$). However, in terms of runoff ratio HS watersheds show slightly higher decline followed by LS and HR watersheds (Figure 8).

Discussion and Implications

Climate and climate warming directly affect the magnitude, type, and timing of precipitation inputs, when water stored as snow is released as recharge, and how much water is abstracted by vegetation. The drainage efficiency of watersheds, on the other hand, is an intrinsic geological property of the landscape that is not affected by climate or warming (at least on hydrologically relevant timescales) but interacts with those factors that are influenced by climate to define the overall hydrograph and its response to climate change. All of these factors contribute to the historical trends we observe in streamflow regimes in the western US.

Multi-decade changes in streamflow regimes are not uniformly distributed across the western US but vary systematically in both space and time with respect to process-linked controls. Changing climatic regimes are primarily expressed in terms of changes in the amount, type, and timing of precipitation. The greatest decreasing trends in winter streamflow occurred in the rain dominated watersheds (HR), and were directly associated with precipitation changes (Table 2; 3). This suggests that while changes in snow dynamics can be important, trends in the magnitude and timing of precipitation as shown in earlier studies (Regonda*, et al.*, 2005; Mote*, et al.*, 2005; Pederson*, et al.*, 2010) and herein will be first order controls on streamflow response. Despite the warming climate, precipitation increase (particularly in the south west) or decrease (Cascades and parts of Rockies) is the major driver of snow accumulation and melt (Mote*, et al.*, 2005; Pederson*, et al.*, 2010). The declines in fall and winter season streamflow in rain dominated watersheds (Table 2) may have contributed to the shift in flow timing toward later in the year as reported by Stewart et al. (2005).

Consistent with a well-founded interpretation of diminished and earlier melting snowpacks (Stewart*, et al.*, 2005; Mote*, et al.*, 2005) in snow and mixed-snow rain dominated watersheds the dominant hydrograph changes we report are declines in spring and summer season streamflow (Table 2; Figure 5). These changes likely reflect reduced snow accumulation and earlier melt-out leading to earlier annual recessions. For areas with no net change in summer precipitation, summer streamflow in rain-dominated watersheds appears to be less sensitive than in snowmelt driven watersheds. These results are broadly consistent with other analyses of historical trends in streamflow from the western US (Ragonda et al., 2005; Stewart et al., 2005). However, the increase in streamflow during winter is small compared to decline in spring and summer seasons, indicating that the shift in flow timing to earlier during the water year (Stewart*, et al.*, 2005) is primarily driven by the decline in streamflow. Additionally, monthly streamflow in the watersheds that receive precipitation in the form of a rain-snow mixture may be more sensitive than snow dominated watersheds, particularly in late summer. This is consistent with

the "snow at risk" analysis (Nolin and Daly, 2006) which identifies "warm" snow packs, i.e., snow accumulation occurring near 0 ^{o}C as more sensitive to climate warming.

This study adds an important new dimension to the interpretation of streamflow trends, however. Our results demonstrate that broad between-watershed differences in drainage rates exert a first-order control on the magnitude of climate warming effects. In the Western US, underlying geologic controls lead to both fast shallow sub-surface dominated systems and slower deeper groundwater systems (Tague and Grant, 2009; Mayer and Naman, 2011; Tague and Grant, 2004; Jefferson*, et al.*, 2008). The impact of these geologically mediated spatial differences in recession characteristics on streamflow sensitivity to warming has been presented in previous theoretical and modeling studies (Tague and Grant, 2009). Here we confirm for the first time that actual streamflow trends reflect these underlying geological controls on drainage efficiency. We show differences between "fast shallow subsurface" and "slow groundwater systems" are as important as differences between "rain" and "snow" dominated watersheds in evaluating streamflow response to climate change, even though they are not directly affected by climate change itself. Our results show that depending on the underlying geology as reflected in *k* values, watersheds with similar precipitation regimes (rain and/or snow) have distinctly different hydrographs, and these differences translate into different historical trends in streamflow changes expressed over multiple decades.

Although changes in late season streamflow are particularly sensitive to geology and timing of recharge, changes in streamflow during other seasons are also important. Some of the largest changes observed, for example, were declines in fall and winter streamflow for high *k*-rain (HR) watersheds, but no major changes in spring and summer streamflow (Figure 5).

Until now, hydrologic modeling has been the most common approach in understanding the hydrologic response of watersheds under climate change. However, future projections made using hydrologic models are associated with model uncertainty, which varies based on model process representation and complexity (Najafi*, et al.*, 2011), and spatial representation (Wenger*, et al.*, 2010). Our results emphasize the importance of accounting for significant differences in drainage rates that occur within the Western US. Since drainage rates are often calibrated hydrologic parameters, this suggests that calibration strategies must explicitly account for these geologically mediated differences (Tague*, et al.*, 2012). Regional scale climate projections of low flows using hydrologic models that do not explicitly account for geological controls in model parameterization are likely to be erroneous. Our results may be useful in ungaged watersheds where very little or no information is available about flow regimes. By incorporating geology, which generally varies at a finer spatial scale than temperature and precipitation, areas of greater or lesser streamflow vulnerability to climate warming can be identified, at least to a first order, particularly in ungaged watersheds where models cannot be calibrated.

Climate is changing and already having demonstrable impacts on the hydrology of streams across the western US. Trends in key hydrologic variables vary across the landscape and depend not only on where "snow-at-risk" is located – which is widely viewed as the overarching control, but also on landscape-level variations in drainage efficiency. These differences in drainage efficiency, which are largely due to intrinsic topographic and geologic settings and factors – are not likely to change under future climates, but nonetheless exert a first-order control on the magnitude and direction of climate change impacts on streamflow. A more pronounced and accurate picture of where water is likely to be in the future must rely on a convolution of both

extrinsic (i.e., climate) and intrinsic (i.e., drainage properties) in developing landscape-level assessments of future streamflow regimes. Similarly, management and adaptation strategies to reduce or mitigate climate impacts should draw upon this broader landscape perspective.

References

Adam JC, Hamlet AF, Lettenmaier DP. 2009. Implications of global climate change for snowmelt hydrology in the twenty-first century. *Hydrological Processes* **23**(7):962-972.

Aguado E, Cayan D, Riddle L, Roos M. 1992. Climatic fluctuations and the timing of west coast streamflow. *Journal of Climate* **5**(12).

Arnell NW. 1992. Factors controlling the effects of climate change on river flow regimes in a humid temperate environment. *Journal of Hydrology* **132**(1-4):321-342.

Arnold JG, Allen PM, Muttiah R, Bernhardt G. 1995. Automated base flow separation and recession analysis techniques. *Ground Water* **33**(6):1010-1018.

Barnett TP, Pierce DW, Hidalgo HG, Bonfils C, Santer BD, Das T, Bala G, Wood AW, Nozawa T, Mirin AA *et al*. 2008. Human-induced changes in the hydrology of the western United States. *Science* **319**(5866):1080-1083.

Cayan DR, Kammerdiener SA, Dettinger MD, Caprio JM, Peterson DH. 2001. Changes in the onset of spring in the western United States. *Bulletin of the American Meteorological Society* **82**(3):399-415.

Déry SJ, Stahl K, Moore R, Whitfield P, Menounos B, Burford JE. 2009. Detection of runoff timing changes in pluvial, nival, and glacial rivers of western Canada. *Water Resources Research* **45**(4):W04426.

Dettinger MD, Cayan DR. 1995. Large-scale atmospheric forcing of recent trends toward early snowmelt runoff in California. *Journal of Climate* **8**(3):606-623.

Duan Q, Schaake J, Andréassian V, Franks S, Goteti G, Gupta HV, Gusev YM, Habets F, Hall A, Hay L *et al*. 2006. Model Parameter Estimation Experiment (MOPEX): An overview of science strategy and major results from the second and third workshops. *Journal of Hydrology* **320**(1-2):3-17.

Hamlet AF, Lettenmaier DP. 2005. Production of temporally consistent gridded precipitation and temperature fields for the continental United States. *Journal of Hydrometeorology* **6**(3):330-336.

Hamlet AF, Lettenmaier DP. 2007. Effects of 20th century warming and climate variability on flood risk in the western U.S. *Water Resources Research* **43**(6):W06427.

Hidalgo HG, Das T, Dettinger MD, Cayan DR, Pierce DW, Barnett TP, Bala G, Mirin A, Wood AW, Bonfils C *et al*. 2009. Detection and attribution of streamflow timing changes to climate change in the western united states. *Journal of Climate* **22**(13):3838-3855.

IPCC. 2007. *Climate change 2007:* Impacts, adaptation and vulnerability. Contribution of working group II to the fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC), Parry *et al.* (eds.).Cambridge University Press. Cambridge, UK, 982.

Jefferson A, Nolin A, Lewis S, Tague C. 2008. Hydrogeologic controls on streamflow sensitivity to climate variation. *Hydrological Processes* **22**(22):4371-4385.

For Peer Review

Jefferson AJ. 2011. Seasonal versus transient snow and the elevation dependence of climate sensitivity in maritime mountainous regions. *Journal of Geophysical Research* **38**(16):L16402.
Kendall MG. 1975. *Rank correlation methods*. Griffin, London, UK.
Lins HF, Slack JR. 1999. Streamflow trends in the United States. *Journal of Geophysical Research* **26**(2):227-230.
Livneh B, Rosenberg EA, Lin C, Mishra V, Andreadis KM, Lettenmaier DP. 2012. Extension and spatial refinement of a long-term hydrologically based dataset of land surface fluxes and states for the conterminous United States. *Journal of Climate (in review)*.
Luce CH, Holden ZA. 2009. Declining annual streamflow distributions in the Pacific northwest United States, 1948-2006. *Journal of Geophysical Research* **36**(16):L16401.
Mann HB. 1945. Nonparametric tests against trend. *Econometrica* **13**(3):245-259.
Mayer TD, Naman SW. 2011. Streamflow response to climate as influenced by geology and elevation. *Journal of the American Water Resources Association* **47**(4):724-738.
McFarland WD. 1983. A description of aquifer units in western Oregon, U.S. Geological Survey, Open-File Report 82-165.
Mote PW, Hamlet AF, Clark MP, Lettenmaier DP. 2005. Declining mountain snowpack in western north america. *Bulletin of the American Meteorological Society* **86**(1):39-49.
Najafi MR, Moradkhani H, Jung IW. 2011. Assessing the uncertainties of hydrologic model selection in climate change impact studies. *Hydrological Processes* **25**(18):2814-2826.
Nijssen B, O'Donnell G, Hamlet A, Lettenmaier D. 2001. Hydrologic sensitivity of global rivers to climate change. *Climatic Change* **50**(1):143-175.
Nolin AW, Daly C. 2006. Mapping "at risk" snow in the Pacific northwest. *Journal of Hydrometeorology* **7**(5):1164-1171.
Pederson GT, Gray ST, Ault T, Marsh W, Fagre DB, Bunn AG, Woodhouse CA, Graumlich LJ. 2010. Climatic controls on the snowmelt hydrology of the northern rocky mountains. *Journal of Climate* **24**(6):1666-1687.
Posavec K, Bačani A, Nakić Z. 2006. A visual basic spreadsheet macro for recession curve analysis. *Ground Water* **44**(5):764-767.
Regonda SK, Rajagopalan B, Clark M, Pitlick J. 2005. Seasonal cycle shifts in hydroclimatology over the western united states. *Journal of Climate* **18**(2):372-384.
Schaake J, Duan Q, Koren V, Hall A. 2001. Toward improved parameter estimation of land surface hydrology models through the Model Parameter Estimation Experiment (MOPEX). *IAHS Publ.* **270**:91– 97.
Sen PK. 1968. Estimates of the regression coefficient based on kendall's tau. *Journal of the American Statistical Association* **63**:1379–1389.
Slack JR, Lumb AM, Landwehr JM. 1993. Hydroclimatic data network (HCDN): A U. S. Geological Survey streamflow data set for the United States for the study of climate variation, 1874– 1988. U.S. Geological Survey Water Resources Investigation Report 93-4076.
Stewart IT, Cayan DR, Dettinger MD. 2005. Changes toward earlier streamflow timing across western north america. *Journal of Climate* **18**(8):1136-1155.
Sujono J, Shikasho S, Hiramatsu K. 2004. A comparison of techniques for hydrograph recession analysis. *Hydrological Processes* **18**(3):403-413.

For Peer Review

Tague C, Grant G, Farrell M, Choate J, Jefferson A. 2008. Deep groundwater mediates streamflow response to climate warming in the oregon cascades. *Climatic Change* **86**(1):189-210.

Tague C, Grant GE. 2004. A geological framework for interpreting the low-flow regimes of cascade streams, Willamette river basin, Oregon. *Water Resources Research* **40**(4):W04303.

Tague C, Grant GE. 2009. Groundwater dynamics mediate low-flow response to global warming in snow-dominated alpine regions. *Water Resources Research* **45**(7):W07421.

Tague CL, Choate J, Grant GE. 2012. Estimating streamflow responses to climate variability in data limited environments: The importance of hydrologic parameter uncertainty in the western Oregon cascades. *Hydrology and Earth System Sciences Discussions.* doi:10.5194/hessd-9-8665-2012.

Tallaksen LM. 1995. A review of baseflow recession analysis. *Journal of Hydrology* **165**(1-4):349-370.

Walker GW, MacLeod NS, Miller RJ, Raines GL, Connors KA. 2003. Spatial Digital Database for the Geologic Map of Oregon, U.S. Geological Survey, Menlo Park, California

Wallis JR, Lettenmaier DP, Wood EF. 1991. A daily hydroclimatological data set for the continental United States. *Water Resources Research* **27**(7):1657-1663.

Wenger SJ, Luce CH, Hamlet AF, Isaak DJ, Neville HM. 2010. Macroscale hydrologic modeling of ecologically relevant flow metrics. *Water Resources Research* **46**(9):W09513.

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Table 1: Characteristics of selected low *k* (L) and high *k* (H) watersheds, grouped by precipitation regimes as rain (R), mixture of rain and snow (M) and snow (S).

Watershed Classification	Number	Hydrologic characteristics											
		Gage Elevation (m)		Annual Precipitation (mm)		Annual Streamflow (mm)		Summer /Annual Streamflow (%)		Fraction of Precipitation Falling as Snow (%)		k (day^{-1})	
Low k (Groundwater dominated)		Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.
LR	5	180	190	1085	969	592	983	4	2	2.8	2.4	0.043	0.012
LM	24	394	344	1660	881	1140	879	10	5	29.3	8.2	0.041	0.019
LS	25	974	663	1398	781	930	812	20	6	59.9	10.2	0.041	0.021
High k (Surface flow dominated)													
HR	9	74	62	1916	774	1366	798	3	2	3.8	2.0	0.085	0.020
HM	9	653	572	1760	814	1367	849	9	7	32.6	10.3	0.076	0.012
HS	9	950	638	1242	307	758	227	12	4	62.1	13.8	0.076	0.008

Table 2: Median absolute (mm) and relative[a] (%) trends[b] over the period 1950-2010 in total monthly, seasonal, and annual streamflow for all watersheds in each hydro-geologic regime.

Streamflow Trend		Monthly												Seasonal				Annual
Low k (Groundwater dominated)		Jan	Feb	March	April	May	June	July	Aug	Sep	Oct	Nov	Dec	Fall	Winter	Spring	Summer	
LR (n = 5)	mm	-0.11	5.00	8.40	1.31	0.79	0.41	0.37	*0.11*	0.00	**0.27**	0.36	-0.11	0.86	19.99	2.56	0.51	37.62
	%	-0.4	12.8	19.8	5.4	6.8	9.0	19.0	12.9	0.0	15.2	5.3	-0.7	5.3	39.9	11.0	32.1	34.5
LM (n = 24)	mm	-1.06	**-31.46**	*3.11*	*-16.18*	**-20.20**	*-15.90*	**-7.83**	**-3.73**	**-3.4***	**-6.86**	-5.43	-8.62	*-37.74*	-6.96	**-51.30**	**-20.19**	**-145.40**
	%	-0.8	-25.4	2.5	-14.3	-19.8	-22.1	-28.7	-21.4	-21.1	-26.1	-8.6	-7.4	-20.7	-1.7	-20.3	-36.2	-15.6
LS (n = 25)	mm	-0.02	-2.37	*6.62*	0.75	-15.61	**-43.46**	**-24.06**	**-5.81**	*-2.49*	*-2.31*	-0.61	-1.74	-5.74	3.00	*-59.54*	**-34.5***	*-131.54*
	%	-0.1	-13.7	27.6	1.3	-10.9	-30.2	-31.8	-18.6	-14.6	-16.4	-3.9	-9.9	-13.2	6.4	-16.7	-32.7	-22.5
High k (Surface flow dominated)																		
HR (n = 9)	mm	-71.47	**-97.0***	*-51.51*	-9.79	2.34	*5.49*	1.38	0.11	*-0.93*	**-15.9***	-11.01	-19.01	-66.68	**-200.70**	0.00	0.00	*-258.72*
	%	-25.3	-44.1	-27.2	-8.4	4.2	20.1	13.8	1.9	-12.3	-47.6	-6.8	-7.0	-15.0	-29.2	0.0	0.0	-18.7
HM (n = 9)	mm	5.64	*-32.02*	*12.85*	*-24.38*	*-27.94*	*-17.39*	*-4.01*	*-3.03*	**-2.89**	**-16.34**	-1.85	-26.58	*-18.10*	**3.00**	**-62.22**	**-15.13**	*-187.25*
	%	3.6	-26.3	12.3	-14.6	-16.5	-15.1	-11.9	-17.2	-11.7	-20.9	-1.3	-16.9	-5.2	0.8	-14.5	-23.9	-13.0
HS (n = 9)	mm	0.63	-3.99	**17.16**	2.17	*-20.89*	**-48.10**	-11.75	-2.40	-1.48	*-2.29*	-1.09	-3.43	-8.03	*9.21*	**-106.10**	**-16.16**	*-159.16*
	%	3.0	-17.5	42.5	2.2	-9.7	-28.1	**-20.7**	-13.9	-12.7	-15.5	-5.4	-15.8	-17.3	12.4	-22.0	-23.6	-23.6
Kruskal-Wallis test		0.010	0.001	0.001	0.000	0.001	0.000	0.000	0.000	0.080	0.482	0.283	0.152	0.014	0.002	0.002	0.000	0.493

[a]calculated as a percentage of median streamflow from 1950-2010
[b]significant trends (p<0.1) in at least 25% (italics), 50% (bold), or 75% (starred bold), of n watersheds

For Review

Table 3: Median absolute (mm) and relative[a] (%) trends[b] over the period 1950-2010 in total seasonal and annual precipitation for all watersheds in each hydro-geologic regime.

Precipitation Trend		Seasonal				Annual
Low *k* (groundwater dominated)		Fall	Winter	Spring	Summer	
LR (n = 5)	mm	-10.4	99.3	-5.9	0.2	54.0
	%	-4.9	23.7	-8.2	2.3	7.6
LM (n = 24)	mm	-35.0	*-65.5*	15.1	*-24.1*	*-102.1*
	%	-6.1	-9.3	6.8	-26.5	-6.5
LS (n = 25)	mm	-6.2	**-97.0**	1.9	-23.3	*-112.4*
	%	-1.9	-24.3	0.8	-20.8	-11.7
High *k* (Surface flow dominated)						
HR (n = 9)	mm	-18.3	**-184.0**	20.1	*-33.2*	-149.2
	%	-2.1	-22.6	6.8	-29.7	-6.9
HM (n = 9)	mm	-33.2	*-68.2*	5.4	*-44.1*	*-108.5*
	%	-4.4	-9.9	1.5	-31.9	-5.5
HS (n = 9)	mm	-40.7	*-43.0*	-9.1	-22.0	*-95.1*
	%	-10.0	-10.0	-3.4	-16.4	-8.3

[a]calculated as a percentage of median streamflow from 1950-2010
[b]significant trends (p<0.1) in at least 25% (italics), or 50% (bold) of n watersheds

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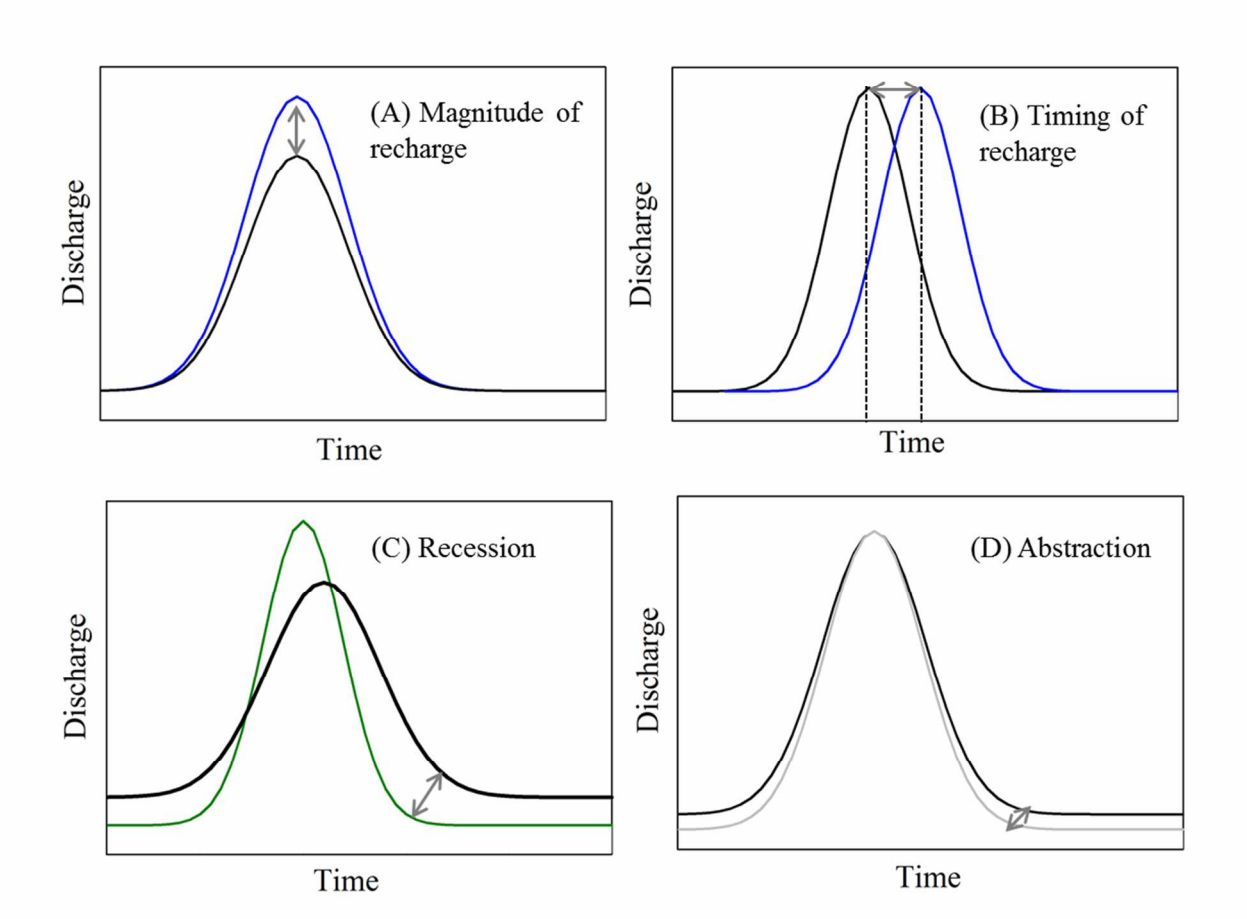


Figure 1: Conceptual annual hydrographs showing influence of individual hydro-geologic controls on the magnitude and timing of discharge. Effects of: changes in climatic regime on magnitude (A) and timing (B) of recharge; C) recession behavior due to differences in geology between basins; and D) abstraction by vegetation. Arrows indicate potential direction of shift in hydrograph.

For Review

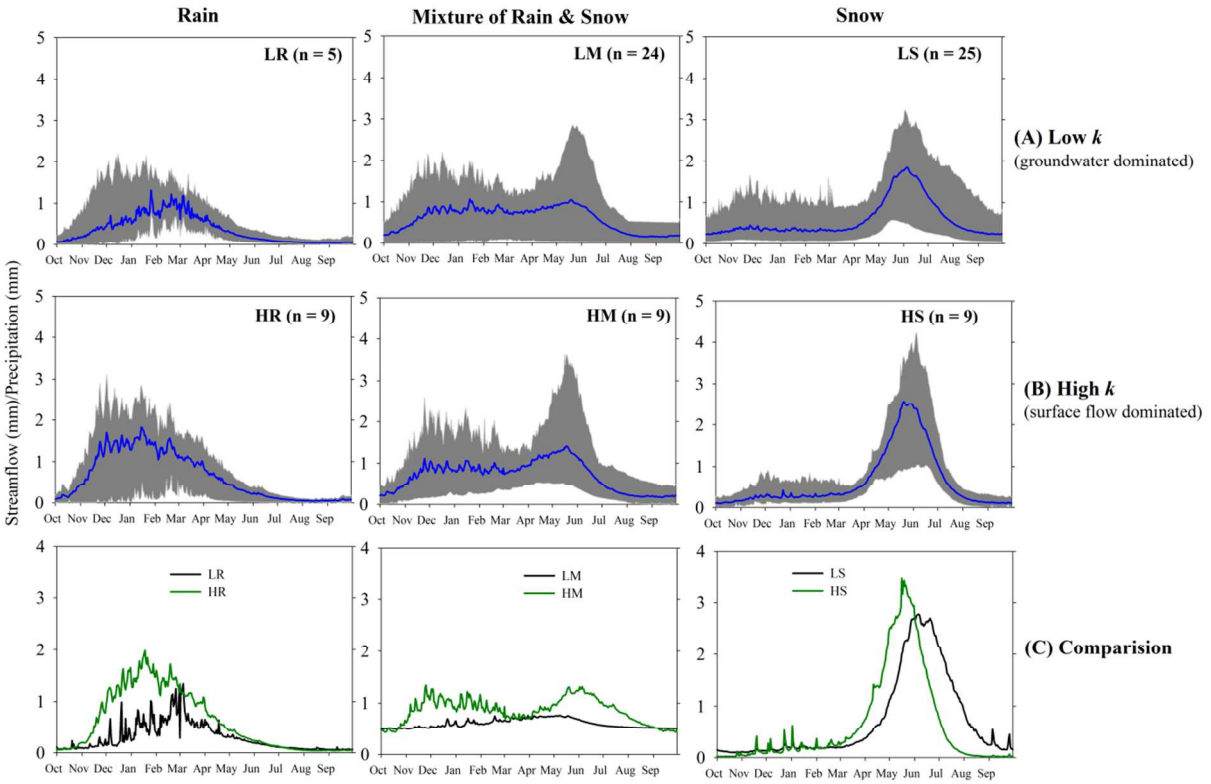


Figure 2: Ensemble average daily hydrographs for each hydro-geologic regime. Average mean daily (blue line) and range of average mean daily (gray area) streamflow for *n* watersheds from 1950 to 2010 shown in top (A) and middle (B) panels. The bottom panel (C) illustrates the difference in average mean daily streamflow between a low *k* (black) and a high *k* (green) watershed from each precipitation regime.

For Review

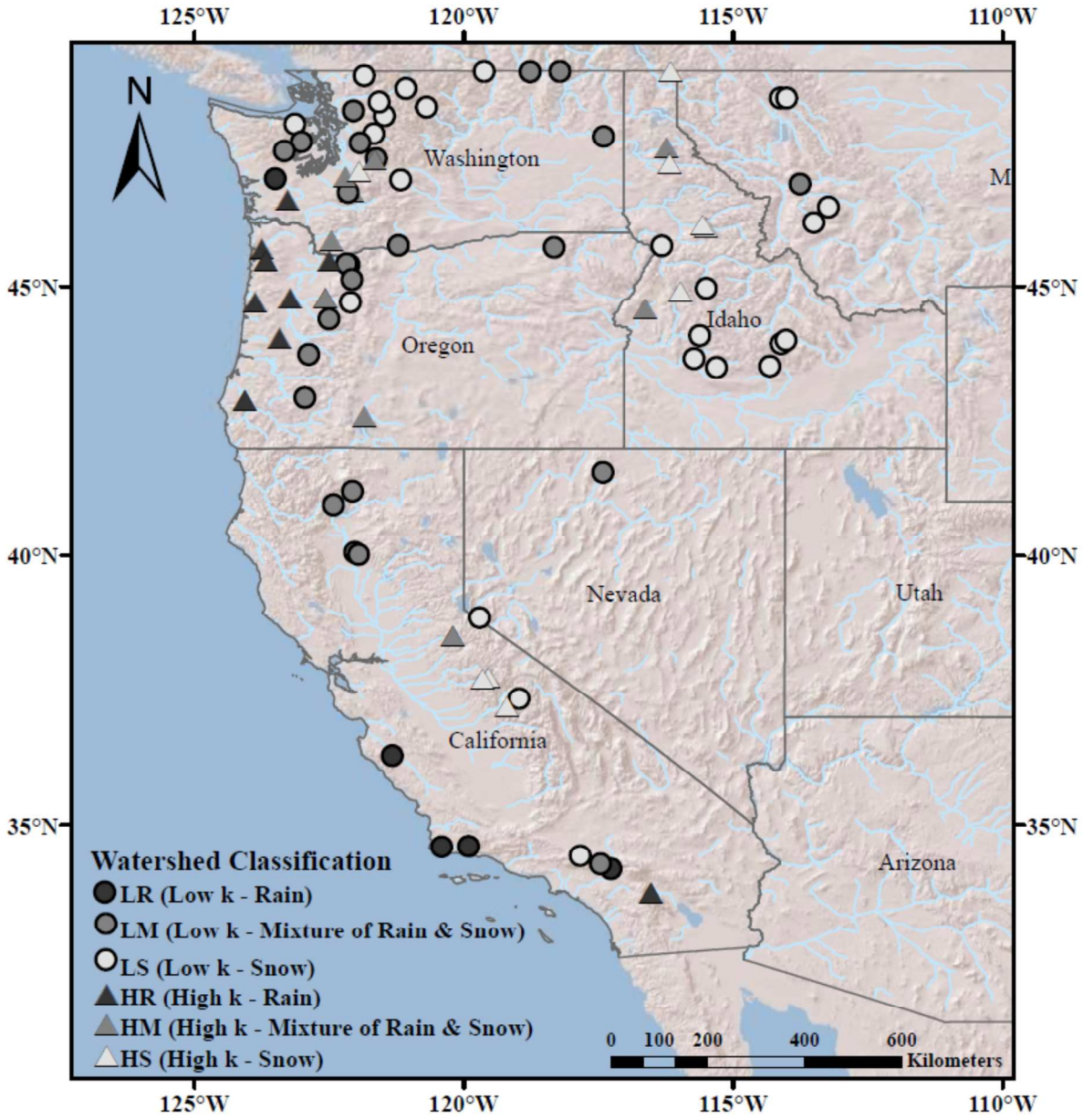
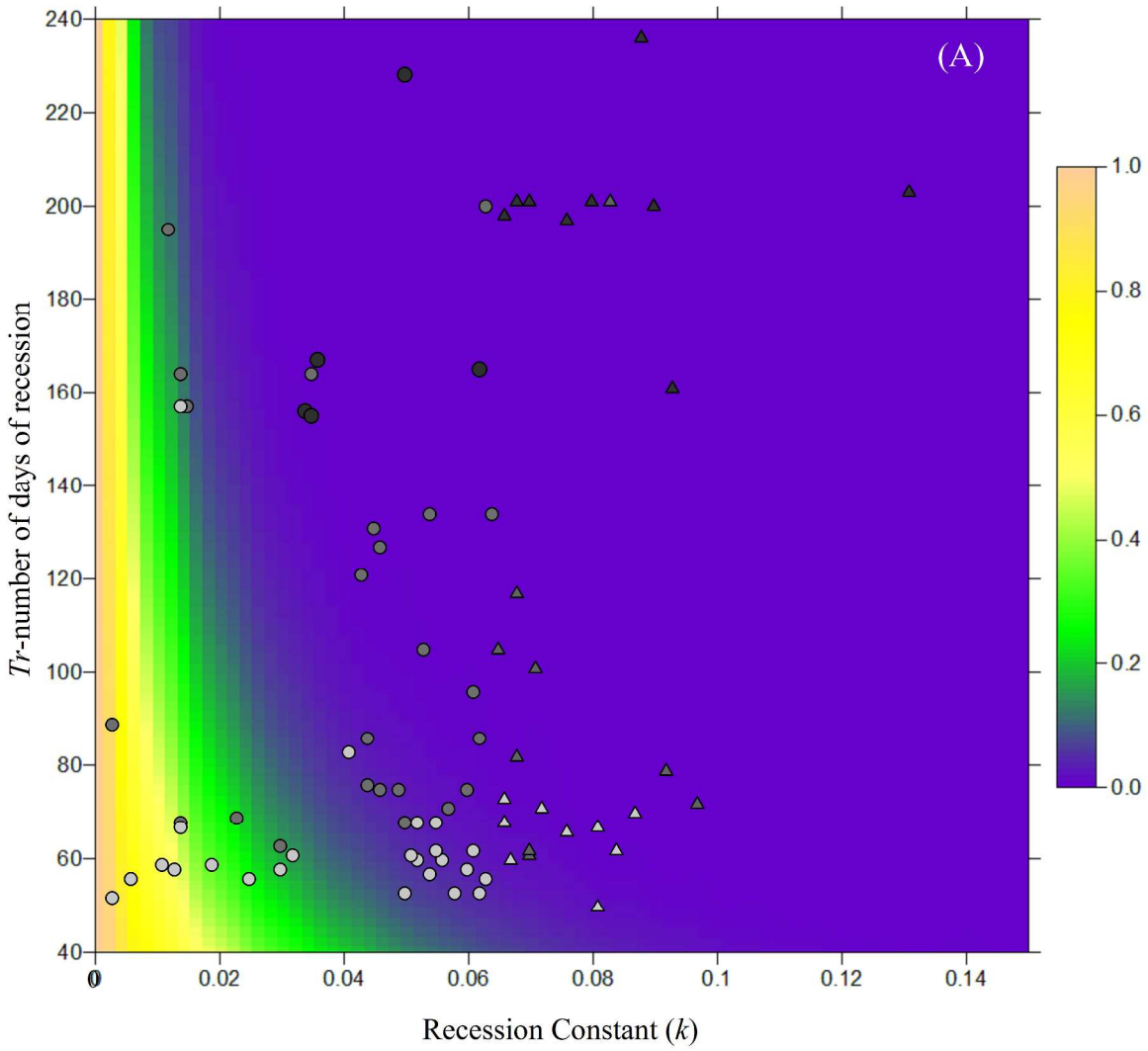


Figure 3: Study age locations classified into hydro-geologic regime by percentage of precipitation falling as snow (S_f) and recession constant (k).


(A)
240
220
200
180
160
140
120
100
80
60
40
0
0.02
0.04
0.06
0.08
0.1
0.12
0.14
Tr-number of days of recession
Recession Constant (k)
1.0
0.8
0.6
0.4
0.2
0.0

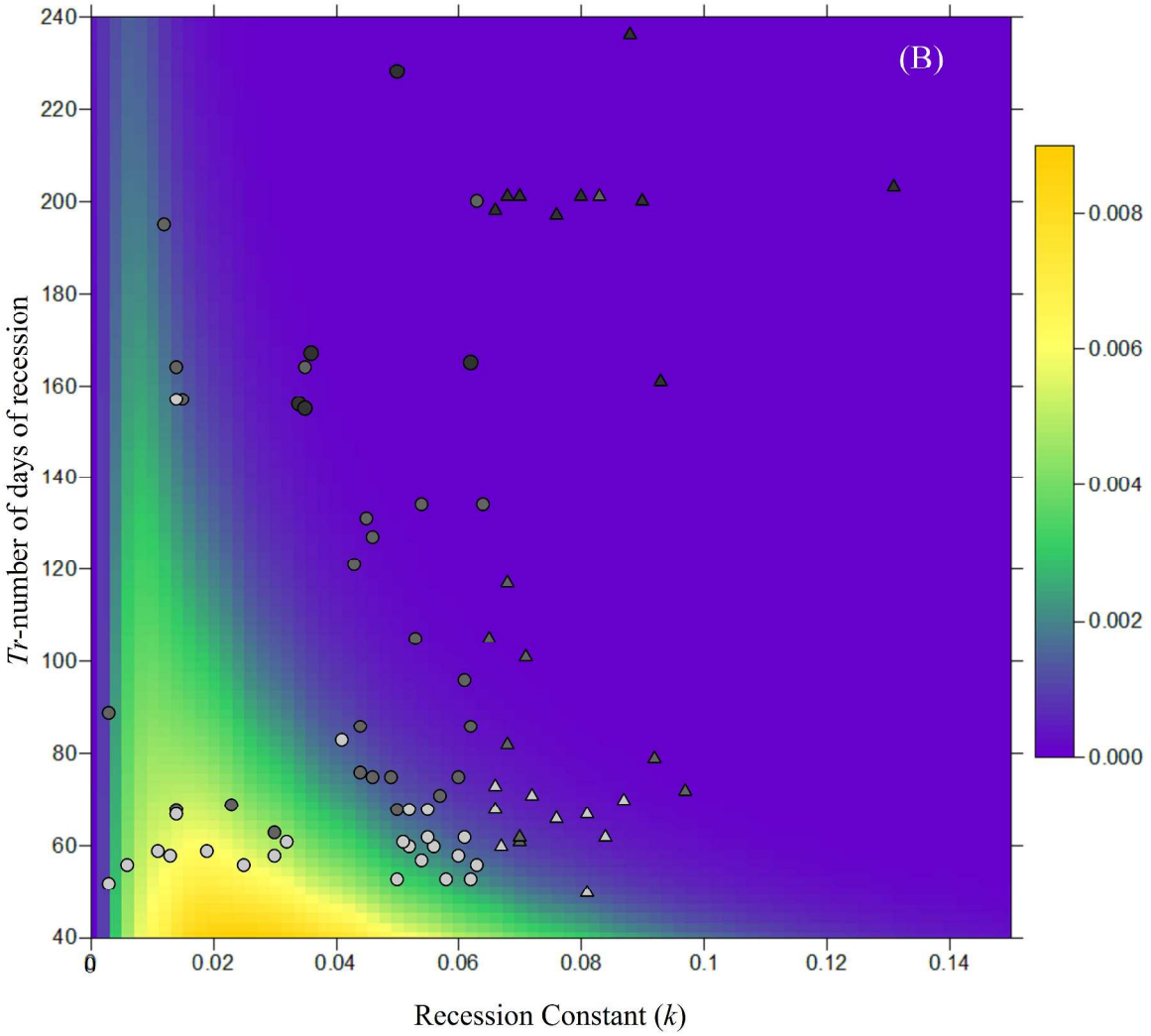


Figure 4: Response surface from conceptual model (Tague and Grant, 2009) of the sensitivity of summer streamflow, to (A) change in the magnitude of recharge and (B) an earlier shift in the timing of recharge. Assuming an initial recharge volume of 1mm, sensitivity is represented as unit change in August 1st streamflow (mm/d), from greatest (yellow) to least (purple) sensitive. Study watersheds are represented as high k (triangle) or low k (circle), gray shading indicates precipitation regime from snow (light) to rain (dark).

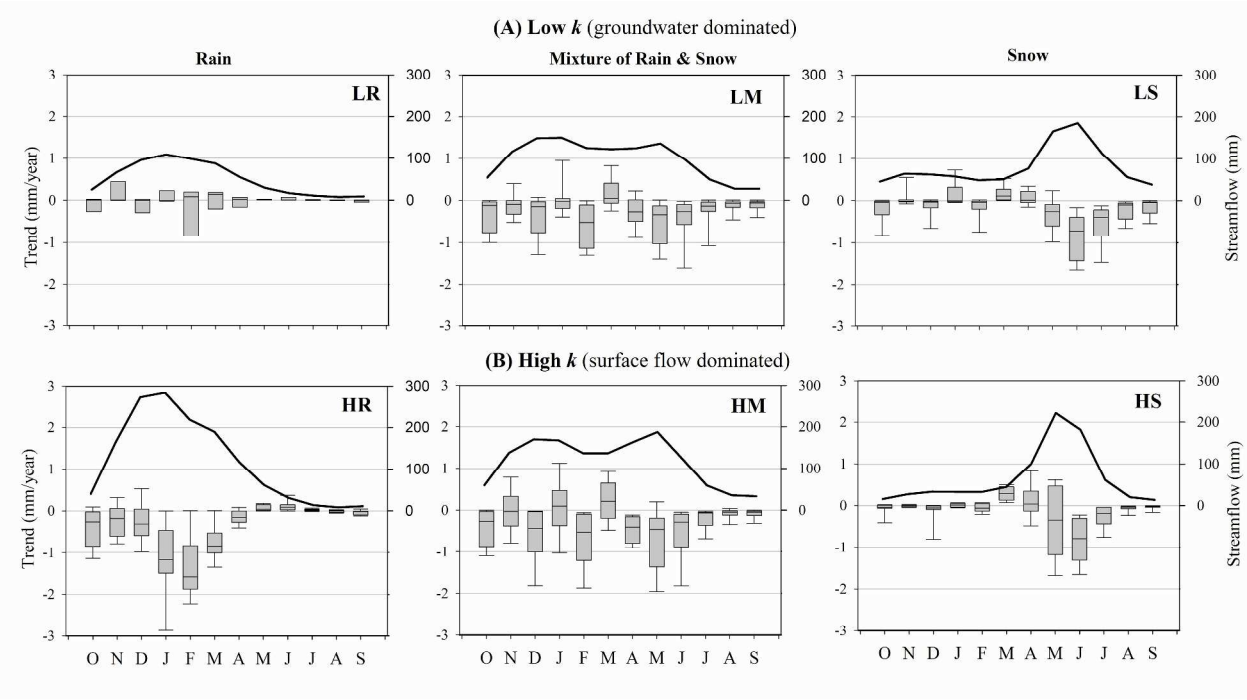


Figure 5: Average monthly streamflow (mm) and trends (mm/yr) for each hydro-geologic regime. Average monthly streamflow (solid black line) is shown on secondary y-axis. Trends in total monthly streamflow are shown as a boxplot. The line inside the box represents the median trend between 1950-2010, the box itself represents the interquartile range (25^{th}-75^{th} percentile range) of the trends, and the whiskers are the 10^{th} and 90^{th} percentiles of the trends. The whiskers for LR watersheds were not calculated because there are only 5 sites.

For Review

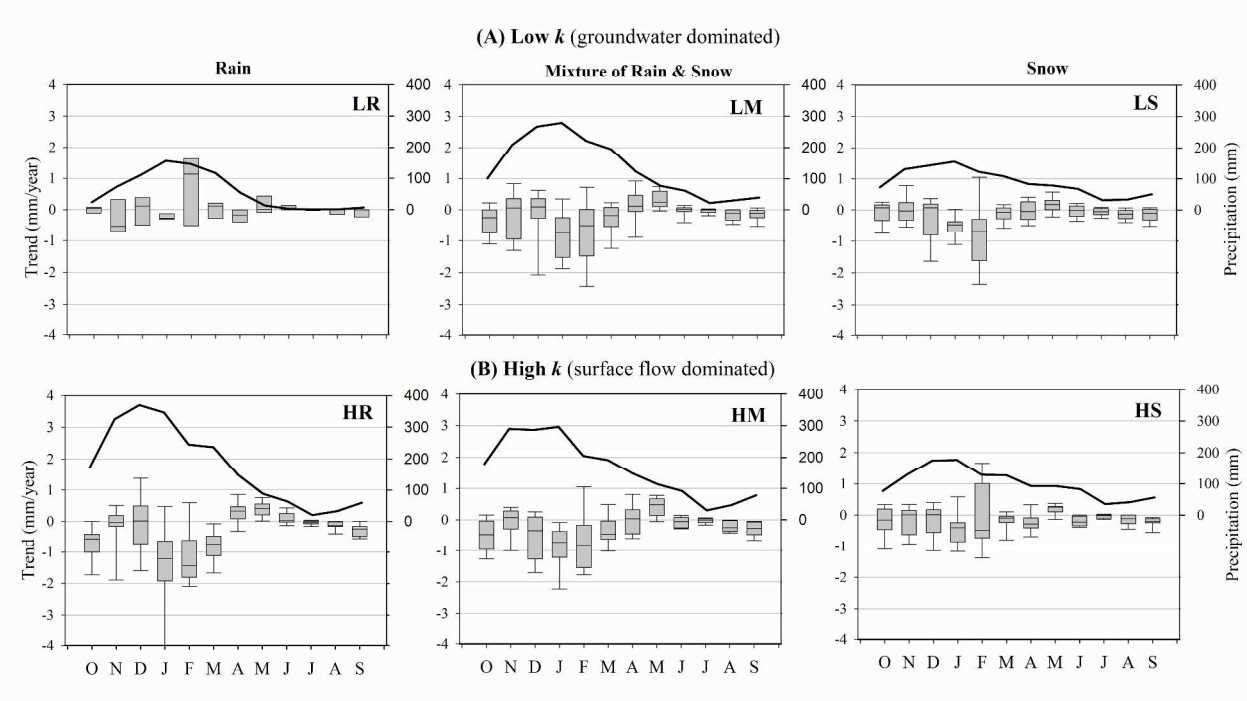


Figure 6: Average monthly precipitation (mm) and trends (mm/yr) for each hydro-geologic regime. Average monthly precipitation (solid black line) is shown on secondary y-axis. Trends in total monthly precipitation are shown as a boxplot. The line inside the box represents the median trend between 1950-2010, the box itself represents the interquartile range (25th-75th percentile range) of the trends, and the whiskers are the 10th and 90th percentiles of the trends. The whiskers for LR watersheds were not calculated because there are only 5 sites.

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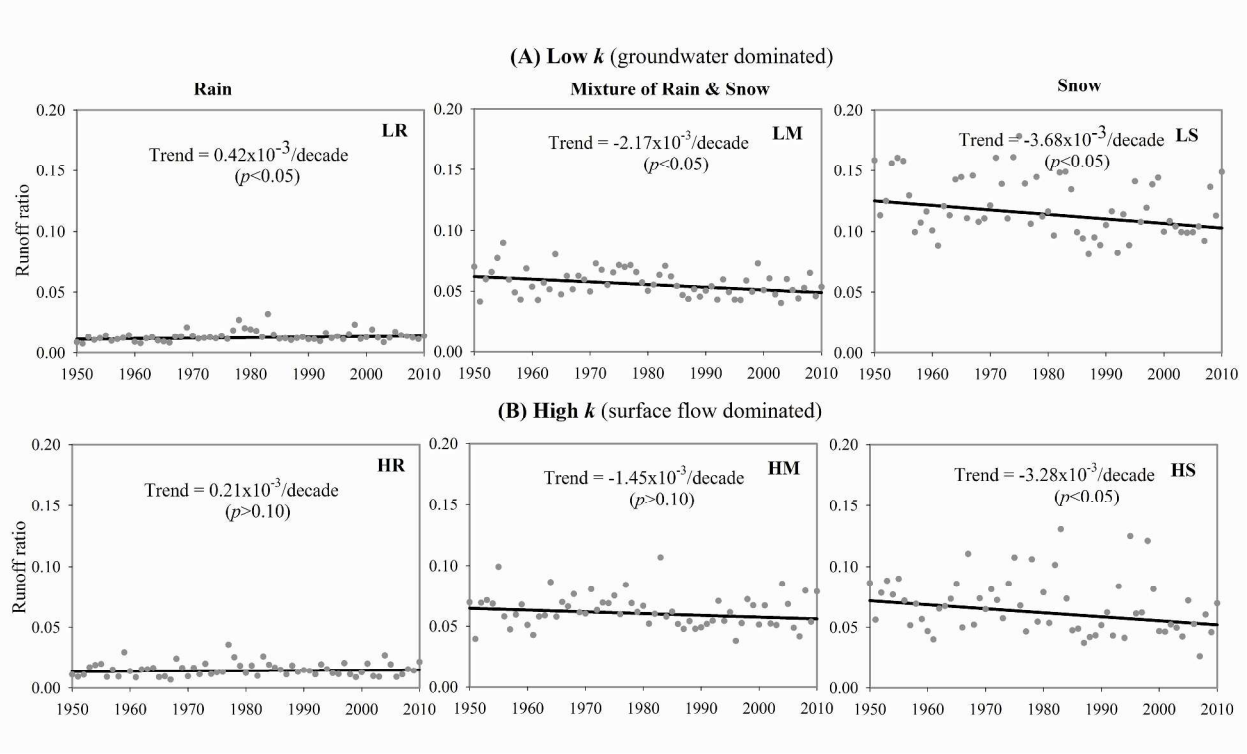

Figure 7: Temporal trends in regional average summer runoff ratios (Q_{summer}/P_{annual}) for each hydro-geologic regime.

For Review

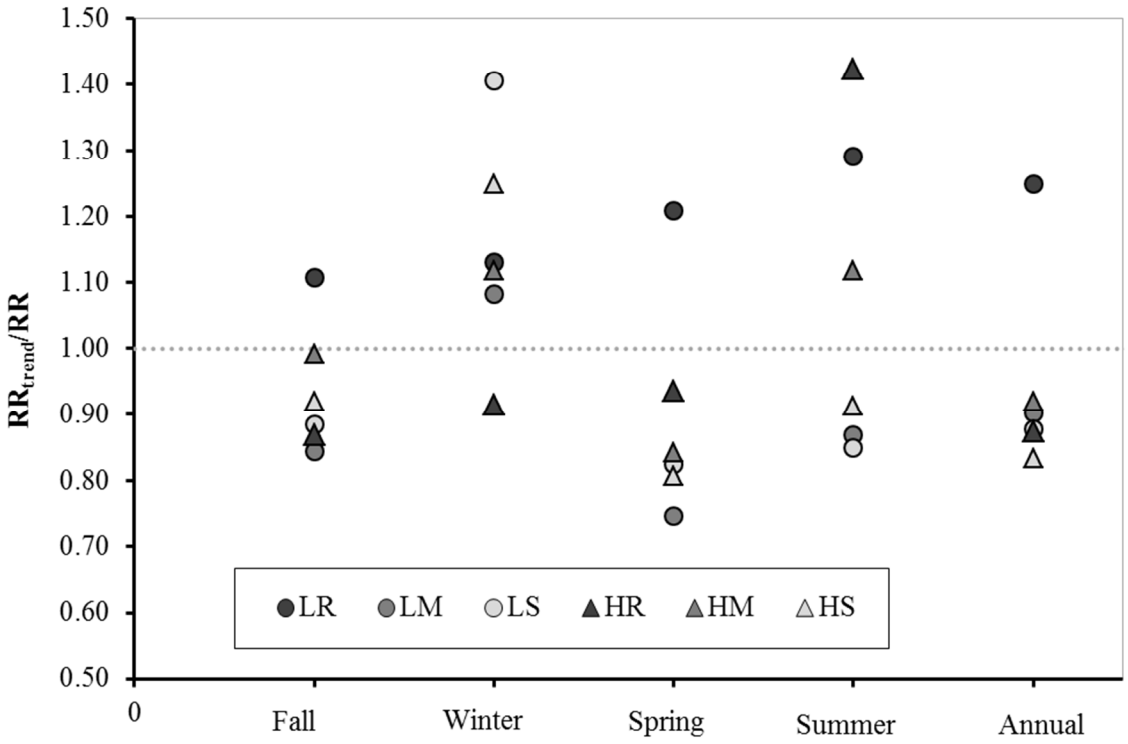

Figure 8: Long-term (1950-2010) seasonal and annual runoff ratio (RR) calculated as the ratio of median streamflow to median precipitation for each hydro-geologic regime. RR_{trend} was calculated after adding or subtracting the calculated change over the historical period (trend (mm/year) X 61 years) to the historical median streamflow and precipitation. A RR_{trend}/RR >1 means increase in runoff ratio and vice versa.

For Review

Uncertainties in VIC streamflow for small watersheds in Oregon and Washington: impacts of driving data, resolution, and groundwater

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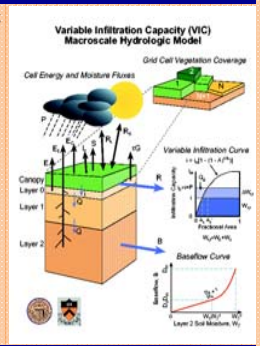
1. Introduction

- An assessment of modeling uncertainties is as important as predictions of direction, magnitude, and timing of future streamflow changes under climate change.
- Either over- or under-estimates of future streamflow could pose problems for decision makers who use model results to guide planning and adaptation measures.
- Identifying the sources (e.g. structural, parametric, or forcing) of modeling uncertainty is essential for constraining model forecasts and improving future streamflow predictions.
- In Pacific North West, examples of uncertainty analysis for climate impacts studies on hydrology using large scale hydrologic models are limited and require attention.
- In addition, role of deep groundwater as it relates to climate change on model performance needs to be evaluated.

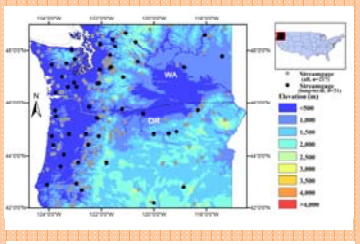
2. Model Background

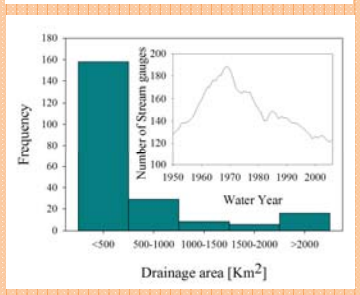
- **V**ariable **I**nfiltration **C**apacity (**VIC**) (Liang et al. 1994) is a macroscale grid base land surface hydrologic model widely used in climate change studies across the US, specifically in PNW.
- The VIC model accounts for sub-grid scale variability in soil, vegetation, precipitation, and topography
- Solves surface water balance and energy balance at every time-step and pixel resolution.
- The model uses a 2-layer energy based snow model for the simulation of snow accumulation and melt.
- Fluxes of daily or sub-daily runoff, baseflow, and evapotranspiration are generated for each pixel independently.



3. Description of Test Basins

- We identified 217 USGS gaging stations in the state of OR and WA to serve as uncertainty assessment sites.
- We have only selected the gages with minimal anthropogenic flow alteration and at least 20 years of daily streamflow record between 1950-2010.
- Fifty one of these watersheds were identified as long-term gage with complete daily streamflow record between 1950-2010.
- These fifty one long-term gages were further classified into 3 groups with varying groundwater contribution.
- Number of stream gage during any given year varies between 189 in 1969 to 121in 2005.
- The majority of the watersheds (~75%) have an area less than 500 km^2.





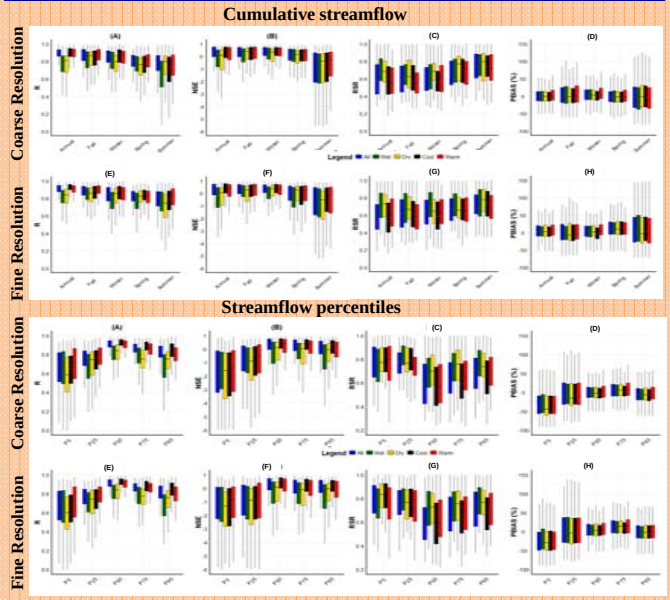
4. Uncertainty Analysis

- We have utilized the simulated streamflow from VIC applied at a coarse (1/16^o lat. x 1/16^o long.) and fine (1/120^o lat. x 1/120^o long.) spatial resolution over the period of 1950–2006.
- Simulated streamflow at the gage were determined by area weighted summation of the total runoff and base flow values from the VIC grid cells within the watershed boundary.
- To address the uncertainty in VIC simulated streamflow, following four quantitative statistics were utilized:

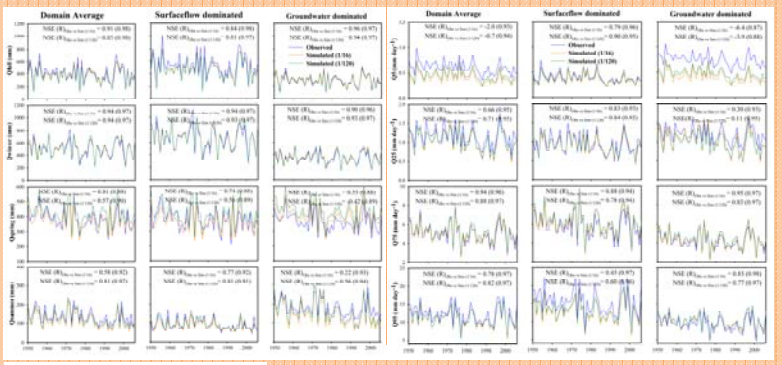
Statistics	Purpose	Value Range	Optimal Value
Spearman rank correlation (R)	To describe the degree of collinearity between simulated and measured data	$-1 \le R \le +1$	1
Nash-Sutcliffe efficiency (NSE)	To describe the relative magnitude of modeling error compared to the measured data variance	$\infty - < NSE \le +1$	1
Percent bias (PBIAS)	To describe the average tendency of the simulated data to be larger or smaller than their observed counterparts	$-100 \le PBIAS < +\infty$	0
Ratio of the root mean square error to the standard deviation of measured data (RSR)	To describe the root mean square error relative to the standard deviation in observed data	$RSR \ge 0$	0

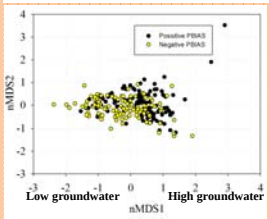
- We have compared the observed and simulated annual and seasonal cumulative streamflow along with five flow percentiles (5, 25, 50, 75, and 95) estimated using daily streamflow during:
  - 1) All years
  - 2) Split between wet and dry years, defined based on total annual precipitation.
  - 3) Split between cool and warm years, defined based on minimum wet day temperature during winter (Oct-March).

5. Results: (A) Improved model prediction at fine resolution; greater uncertainty in dry season runoff.



(B): Over and under-prediction is large in groundwater dominated watersheds

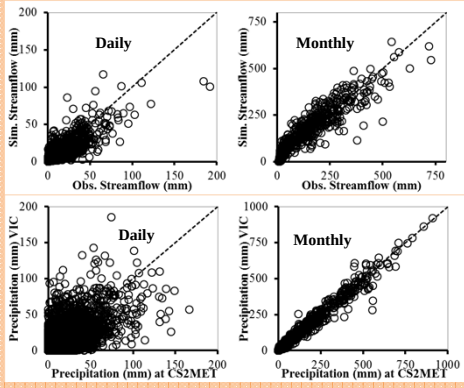




- Greater uncertainty in spring (over-predicted) and summer (under-predicted) discharge, particularly in groundwater dominated watersheds.
- Non-metric Multidimensional Scaling (N-MDS) ordination shows that positive (over-prediction) and negative (under-prediction) biases are significantly associated with the level of groundwater.
- Low flows (5th percentile) are under-predicted in groundwater dominated watersheds whereas peak flows (95th percentile) are under-predicted in surface flow dominated watersheds.

(C). Not all the uncertainties are associated with groundwater; driving data shows strong disagreement with observation.

- Geologically, HJA watershed is classified as western cascade meaning very little influence of deep groundwater compared to the watersheds located in high cascades.
- We selected this watershed as a case study to demonstrate the role of driving data on the model performance, other than groundwater.
- Strong disagreement between observed (obs.) and simulated (sim.) streamflow at daily time scale can be attributed to the driving data (i.e. precipitation).
- However, there is a ~25% error in sim. summer and fall streamflow, despite the strong agreement in monthly and seasonal (~2% error) precipitation.
- This analysis indicates that the modeling uncertainties are not limited to groundwater dominated watersheds.



6. Summary

- We have demonstrated that the direction of uncertainties (over- or under-prediction) in simulated late season streamflow is directly dependent on the presence and absence of groundwater, particularly at seasonal time scale.
- Since groundwater dominated watersheds are most sensitive to climate change, projection using VIC model under given future climate change scenario could have been largely underestimated.
- Quantifying the streamflow uncertainties and how it relates to driving data, resolution, and groundwater is the key step forward toward reducing the modeling uncertainties and making accurate climate change impact assessment.

7. References

Liang, et al., A Simple hydrologically Based Model of Land Surface Water and Energy Fluxes for GSMs, J. Geophys. Res., 99(D7), 14,415-14,428, 1994.